Applying the Multi-Layer Perceptron Neural Network Model to Predicting School Closures: An Example of Taipei City

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ABSTRACT

In this study, we utilised multi-layer perceptron neural networks (MLPNNs) to assess the issue of school closures. Specifically, this study uses the MLPNN model to conduct learning assessments to identify schools that may suffer from poor management. The empirical findings are briefly summarised as follows: (1) The research shows that more than half of the private schools in this study will face bankruptcy. In Taipei City, out of the 23 existing private schools, only four operate normally, while the remaining 19 private vocational high schools require assistance. About 12 schools face severe problems in terms of poor management, accounting for 63% of the total, while seven schools had a prediction value below 50, indicating a severe problem. These schools have expressed an immediate need for government assistance. (2) According to the MLPNN model in this study, reducing the number of full-time teachers is a primary factor contributing to school closures. First, since full-time teachers are a fixed cost, the dismissal of teachers tends to be prioritised to bring down school management costs. This, in turn, reduces the teacher-student ratio. Other factors that contribute to school bankruptcy are dismissing staff and part-time teachers, reducing expenditure, and poor operational maintenance. When the above policies are implemented in schools with poor management, a vicious cycle is created, leading to the bankruptcy of schools.

KEYWORDS: *multilayer perceptron neural networks, predicting school closure; school closures, high education, population decline*

JEL CLASSIFICATION: *C45, D61, I21, I28*

1. INTRODUCTION

The closure of schools in rural areas has become a common occurrence, primarily attributed to the significant rural-to-urban migration that has taken place over the last 50 years. This migration has been driven by the industrialisation of agriculture and the rapid consolidation and globalisation of industries. As a result, many schools established in the 1950s and 1960s have had to shut down (Collins et al., 2019; Egelund & Laustsen, 2006).

In Taiwan, the educational landscape has undergone a transformation, compounded by a declining birth rate, which has had a severe impact on the viability and development of private secondary schools. Currently, Taiwan is home to approximately 513 public and private vocational high schools, with private institutions accounting for more than 50% of this total. Despite the challenges, these private schools continue to play a crucial role in the education market.

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According to the Department for Education of Taiwan (2020), high school enrolment has plummeted, with a reduction of nearly 200,000 students over the past nine years, amid a falling birth rate. More than nine of these high schools have applied for suspension or bankruptcy. Additionally, high school vocational applications have closed down, with Taipei City accounting for only four schools. Furthermore, there has been a severe decline in the birth rate, and private high schools have borne the brunt of the situation, with many famous private schools having lost approximately half of their students in successive years. In the future, Taiwan's low birth rate will impact the enrolment in vocational high schools. It is estimated that more than half of the private vocational high schools in Taipei City face closure in the next six years. In addition, an increasingly high number of private schools are closing down (Kuo, 2019). By 2026, the Ministry of Education expects private school enrolment to fall to 200,000 students, down from about 230,000 last year, putting more than 30 of the nation's 212 private schools at risk of closure.

Numerous research endeavours have delved into examining the sociological mechanisms linked to the closure of schools, primarily prompted by shifts in demographics (Cedering and Wihlborg, 2020; Lehtonen, 2021; Lykke Sørensen et al., 2021; Villa and Knutas, 2020; Villa et al., 2021). However, high schools that have either closed or stopped enrolling students will directly affect students' choice of schools, thus affecting their right to education (Cedering & Wihlborg, 2020; Engberg et al., 2012). Additionally, this will lead to the unemployment of teachers and abandoned schools (Kuo et al., 2015). Therefore, government units actively assist poorly run schools and implement strategies to improve school management. However, they have still been unable to effectively prevent the closure of schools. Therefore, we utilise multi-layer perceptron neural networks (MLPNNs) to estimate the weights of the factors that affect schools and thus identify schools with the potential for crises. This will help the government to aid schools with real problems.

The subsequent sections of this paper are structured in the following manner. The Literature Review section examines the conceptual framework and provides an overview of relevant policies. In the Research Methodology section, the MLPNN methodology is elaborated upon, while the Empirical Results and Analysis section presents the findings of the study. Lastly, the Concluding Remarks section presents the conclusions drawn from this research.

2. MATERIALS AND METHODS

Education is regarded as an industry, which indicates that there is a market for education. If there is a market, then competition exists in this market as well. Thus, schools must compete to survive. They compete in terms of their investment in school reform and by marketing and strengthening their organisation capabilities to enhance school competitiveness, reduce the opportunity for their elimination from the market, and facilitate sustainable management and development of the school (Bailey & Cooper, 2009; Connor, 1999; Kotler & Fox, 1985; Kuo et al., 2015).

However, in the 21st century, it was discovered that the population has repeatedly hit new lows in recent years, resulting in the issue of structural changes in the population and a shortage of students, which has affected the existence of schools. Therefore, the low birth rate has become a trending global problem. In response to the declining birth rate and the reduction in national competitiveness, major advanced countries in the world have implemented relevant educational reforms (Fu & See, 2022; Fu et al., 2019; Gainey & Andressen, 2022), e.g., the transformation of schools into charter schools or international schools. These reforms have indeed been effective in improving the operation and competitiveness of schools (Booker et al., 2011; Fortson et al., 2012; Zimmer et al., 2012). However, these educational reforms take time and will not immediately improve school operations.

In Taiwan, high school enrolment has plummeted by nearly 200,000 students over the past nine years amid a falling birth rate. The number of high school students in 2021 was 609,745, compared to 809,188 in 2011. The Ministry of Education stated that this figure is likely to fall even further, to 553,000 by 2026. The Ministry of Education data showed that more than 100 private schools are at risk of closure over the next five years. Therefore, the government must help poorly run or problematic schools to address this problem. However, considering their reputation, these schools are typically unwilling to accept government assistance and choose to close down naturally, selling their assets, and creating new social problems. Therefore, identifying poorly run schools so that the government can actively assist in school operations is a topic of concern for the future.

Employing the MLPNN model does not require any statistical assumptions about data distribution, and it has demonstrated strong performance in recent studies. Furthermore, it holds considerable promise for nonlinear mapping, adaptive learning, and addressing environmental challenges (Faridatul and Wu, 2018). With the MLPNN model's broad range of applications, various algorithms for managing it are documented in the literature. However, many of these algorithms are specifically tailored for their respective fields and problem applications (Abdollahi et al., 2022; Al-Dousari et al., 2023).

Furthermore, with their remarkable ability to derive meaning from complicated or imprecise data, neural networks can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques (Maind & Wankar, 2014). Some examples of neural networks are a neural-network-based upright frontal face detection system (Rowley et al., 1998); multi-layer perceptron (MLP) neural networks, which have been widely used in automatic credit scoring systems with high accuracy and efficiency (Zhao et al., 2015); using an accurate and reliable neural network model tool to predict COVID-19 confirmed, recovered, and death cases (Namasudra et al., 2021); and 5G network simulation in smart cities using neural network algorithms (Mukherjee et al., 2021; Smys et al., 2021).

Researchers have used neural networks with multi-layered perceptron, regression, and vector autoregression for forecasting in various fields. Hence, the assessment model utilised in this study will assist the government in providing aid to poorly managed schools. An advantage of this study’s MLPNN evaluation model is that it can effectively distinguish and predict poor management, thus helping to reduce the risk of school closures.

School closures may not be an adequate solution when schools are poorly run. Further attention must be paid to the social problems that cause school closures. Therefore, this study utilises the MLPNN model to evaluate the business and management of schools in Taipei City to further identify and analyses problematic schools. Finally, this study can help the government to help poorly managed or problematic schools to manage their situation, thereby allowing them to maintain sustainable operations.

3. RESEARCH METHODOLOGY

This study seeks to identify poorly managed schools among senior high schools and vocational high schools in Taiwan. Therefore, this study employed the MLPNN model to evaluate the business and management of several schools and predict whether they are headed in a poor management direction. Hence, this study's model includes two parts: the MLPNNs analysis and ranking the weights derived from the MLPNN analysis.

3.1 MLPNN method

MLPNNs are the most commonly used feed-forward neural networks due to their rapid operation, ease of implementation, and minor training set requirements (Abushariah et al., 2014; Kocyigit et al., 2008; Orhan et al., 2011; Subasi, 2007). An MLPNN typically comprises three sequential layers, namely the input (e.g., $x = x_1, \dots, x_n$), hidden (e.g., $\sum$), and output layers (e.g., y). Furthermore, in this context, "b" is used to denote bias vectors, which are usually set as b = 1. The symbol "a" represents the net input, and it corresponds to a fusion network that combines the features extracted from each input modality. As mentioned earlier, "∫" is the transfer function employed in the network. Figure 1 provides a visual representation of the ultimate configuration. During the learning process, the network dynamically adapts the weights of the inputs to calculate their updated values.

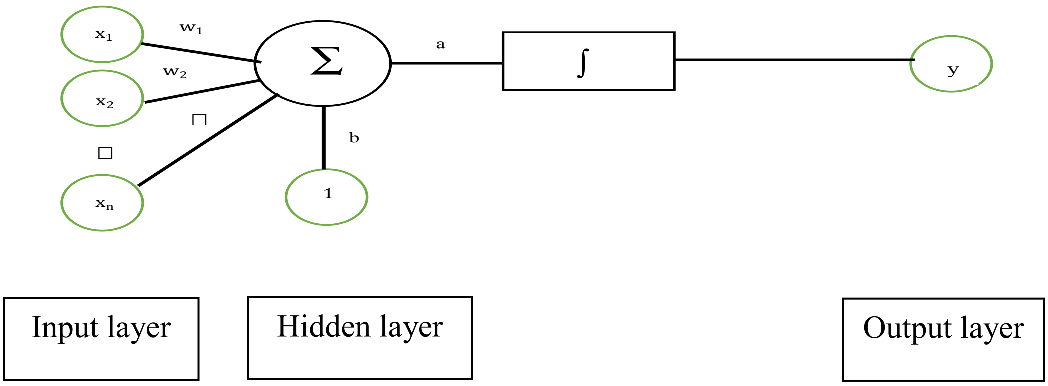

Figure 1. Structure of the MLPNN model used in this study
Source: https://zh.wikipedia.org

The computation of MLPNN is given in Equation (1-2) as follows:

$$a_j = b_j + w_1x_1 + w_2x_2 + \cdots + w_nx_n = b_j + \sum_{i=1}^{n} w_i x_{ji} \quad , j=1, \dots, n \qquad (1)$$

$$y_j = f(a_j) = f(\sum_{i=1}^{n} w_i x_{ji}) \quad , j=1, \dots, n \qquad (2)$$

In the above equations, a is the linear combination of inputs $x_1, x_2, \dots, x_n$, b is the partial weight (bias), $\sum_{i=1}^{n} w_i x_i$ the connection weight between the input x_i, f (a_j) is the activation function, y is the output. The weights of the neural network are updated using a back propagation (BP) algorithm as shown in Equation (3).

$$\sum_{i=1}^{n} w_i(t+1) = w_i(t) - \varepsilon \frac{\partial E_f}{\partial \omega_i}(t) \qquad (3)$$

In the above equation, ε is the learning rate, E_f is the error function. We used Equation (3) to calculate the new weights and re-estimate x_i using the new weights. In this study, we used an MLPNN model with a single hidden layer comprising hidden neurons.

3.2 Model setup

Defining the network architecture: First, we selected a group of possible functions for the learning training process of the neural networks. We defined a suitable network architecture to generate an effective learning model through the training process.

Defining the learning target: A learning objective is important for neural network learning. It is a numerical value used to describe the quality of neural networks. By defining the correct learning objective, we generated a learning model that meets our requirements for the training process.

Training using the numerical method: The actual training process utilised a specific numerical method to determine the best combination of weights for the defined network architecture and to create an index of the learning target that is as small as possible. Stochastic gradient descent (SGD) is typically used to optimise weight combinations and learning objectives. SGD can be viewed as a high-dimensional space with all weight combinations, taking a small step in the descending direction of each dimension at a time. After the same steps were implemented several times, we obtained an appropriate weight combination.

3.3 Formatting of mathematical components

Evaluate new weight values ($\sum_{i=1}^{n} w_{new\,i}\ of\ inputs\ x_{ji}$) by estimating the Equation (3). Hence, the 'rule of thumb' for interpreting MLPNN grade results is as follows: 0 to 0.20 is not at all important, 0.21 to 0.35 is low importance, 0.36 to 0.67 is neutral, 0.68 to 0.90 is important, and 0.91 to 1.00 is considered very important (Taylor, 1990; Shavelson, 1998), the rank of MLPNNs weight results in Table 1.

Table 1. The rank of new weight calculated

No.	New weight value	Variable correlation degree
1	0.91–1.00	Very important
2	0.68–0.90	Important
3	0.36–0.67	Neutral
4	0.21–0.35	Low importance
5	0–0.20	Not at all important

Source: authors' compilation

4. EMPIRICAL RESULTS AND ANALYSIS

The empirical analysis in this study comprised two parts: the adoption of the MLPNN model to evaluate the business and management variables contributing to school closures, and the estimation of the new weights of the results. This was followed by using the new weights to the ranking the schools according to their potential for closure.

4.1 Study objects

This study is mainly applicable to private high schools in Taipei since the sample did not include any public schools. The main reason for this is that private schools' budgets are determined by the number of students they have, unlike public schools, which receive government support. Therefore, when private high schools reduce the number of their students, their school operations are inevitably affected (by the reduction in tuition income).

However, the sample included poorly managed schools. Therefore, we utilised the study sample to assess the risk of bankruptcy of private schools in Taipei City. Subsequently, we calculated the estimated value by differentiating the into two groups: normal schools (with normal operations and no financial crisis) and schools that had already undergone closure.

Additionally, after excluding newly established schools, the selected high schools that remained were transformational vocational high schools. The final sample consisted of 23 schools; their names and attributes are outlined in Table 2.

Table 2. School names and attributes

No.	School name	Attributes	City name	Situation
1	Jin-Gwen High School	Private	Taipei	Normal
2	Tai-Bei High School	Private	Taipei	Normal
3	Jin-Ou Girls High School	Private	Taipei	Normal
4	You-De High School	Private	Taipei	Normal
5	Hu-Jiang High School	Private	Taipei	Normal
6	Yan-Ping High School	Private	Taipei	Normal
7	Qiang-Shu High School	Private	Taipei	Normal
8	Ta-Tung High School	Private	Taipei	Normal
9	We-Go High School	Private	Taipei	Normal
10	Blessed Imelda Girls High School	Private	Taipei	Normal
11	Tsai-Hsing High School	Private	Taipei	Normal
12	Shi-Xin High School	Private	Taipei	Normal
13	We-Sley Girls High School	Private	Taipei	Normal
14	Da-Cheng High School	Private	Taipei	Normal
15	Taipei Fu-Hsing Private High School	Private	Taipei	Normal
16	Da-Ren Girls High School	Private	Taipei	Normal
17	St. Bonaventure Girls High School	Private	Taipei	Normal
18	Hua-Xing High School	Private	Taipei	Normal
19	Dong-shan High School	Private	Taipei	Normal
20	Zhong-Xing High School	Private	Taipei	Closure
21	Lih-Ren High School	Private	Taipei	Closure
22	Dong-Shan High School	Private	Taipei	Closure
23	St. Francis High School	Private	Taipei	Closure

Source: authors' compilation

4.2 Variable selection of the MLPNN model

Before establishing an empirical model, we must list as many preliminary assessment factors for the case as possible. Thus, after referring relevant literatures (Lee & Teng, 2009; Huang, 2013; Liu, Kuo, & Li, 2016; Prasetyia, 2019; Kuo, 2019) and the factors affecting school management efficiency may also connect the issues for school closure or bankruptcy, then we select the following five operational variables related to this issue as MLPNN learning values and a new weight value is estimated.

In this paper, the including four input variables: teacher-student ratio($\boldsymbol{X_1}_{it}$), the number of full-time teachers($\boldsymbol{X_2}_{it}$), the number of part-time teachers($\boldsymbol{X_3}_{it}$) and the number of staff ($\boldsymbol{X_4}_{it}$). There is one output variable: ($\boldsymbol{Y}_{it}$), total number of students , Ultimately, data were being were collected for five variables through eleven years (2011-2021). Finally, write it as Equation (4):

$$\boldsymbol{Y_{it}}(output) = activation\ function\ (\boldsymbol{X_{1_{it}}} \times \boldsymbol{w_1}, \boldsymbol{X_{2_{it}}} \times \boldsymbol{w_2}, \boldsymbol{X_{3_{it}}} \times \boldsymbol{w_3}, \boldsymbol{X_{4_{it}}} \times \boldsymbol{w_4} + b1) \quad (4)$$

The basic factors can be described as follows:

(a) $\boldsymbol{Y}_{it}(Output)$ ：Total numbers of school students (school size) of school $_i$.

(b) $\boldsymbol{X_1}_{it}(Input)$ ：Teacher-student ratio (average number of students per teacher) of school $_i$.

(c) $\boldsymbol{X_2}_{it}(Input)$: Total number of full-time teachers of school $_i$(the number of full-time teachers that are willing to hire).

(d) $\boldsymbol{X_3}_{it}(Input)$: Total number of part-time teachers of school $_i$(the number of part-time teachers that are willing to hire).

(e) $\boldsymbol{X_4}_{it}(Input)$: Total number of staffs of school $_i$(the number of staffs that are willing to hire).

Bias (b1): It defines the neuron's firing threshold in space and is used to increase or decrease the input value's influence.

The new weight values are estimated through Equation (4), and it is substituted into Equation (5) to assess the predicted $\widehat{\boldsymbol{Y}}_{it}$value of the school closures. We then analyse and find problematic schools.

$$\widehat{\boldsymbol{Y}}_{it} = f(\boldsymbol{X_1}_{\boldsymbol{it}} \times \boldsymbol{w}_{\mathbf{new\ 1}}, \mathbf{X}_{\boldsymbol{it}} \times \boldsymbol{w}_{\mathbf{new\ 2}}, \boldsymbol{X_3}_{\boldsymbol{it}} \times \boldsymbol{w}_{\mathbf{new\ 3}}, \boldsymbol{X_4}_{\boldsymbol{it}} \times \boldsymbol{w}_{\mathbf{new\ 4}}) \quad (5)$$

$\widehat{\boldsymbol{Y}}_{it}$: It is estimated the predicted value of the school closures.

$\boldsymbol{w}_{\mathbf{new\ 1}}$~$\boldsymbol{w}_{\mathbf{new\ 4}}$: The actual training process to find the best combination of new weights in the defined network architecture.

4.3 Results of the MLPNN model explaining determinants affecting school closures

We list the MLPNN model training architecture in Figure 2. The prediction accuracy of 96.1% after training with the MLPNN model is shown in Figure 3.

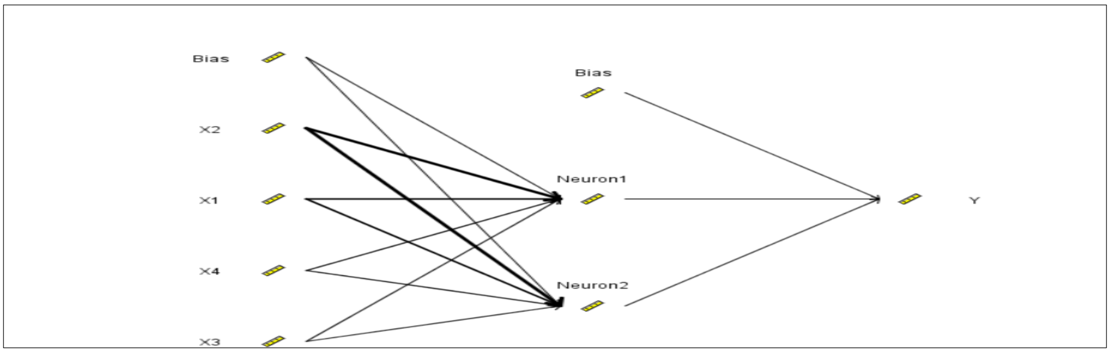

Figure 2. The MLPNN model's training architecture
Source: authors' compilation

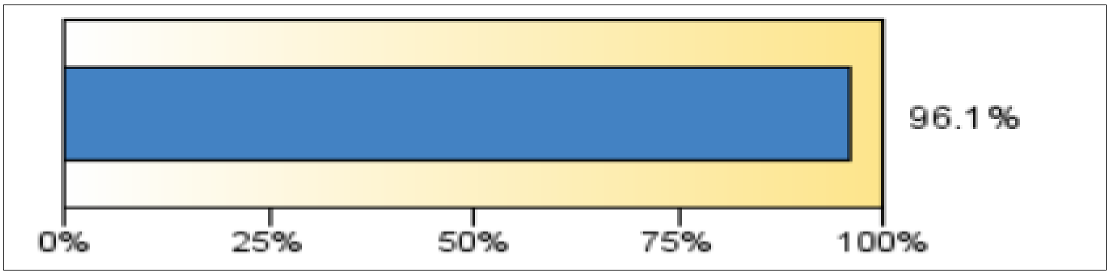

Figure 3. Accuracy of training with the MLPNN model
Source: authors' compilation

Table 3. Results of MLPNN model

Variable	Size of correlation	Interpretation
X_1	0.3159	Neutral
X_2	0.5994	Neutral
X_3	0.0347	Not at all important
X_4	0.1	Not at all important

Source: authors' compilation

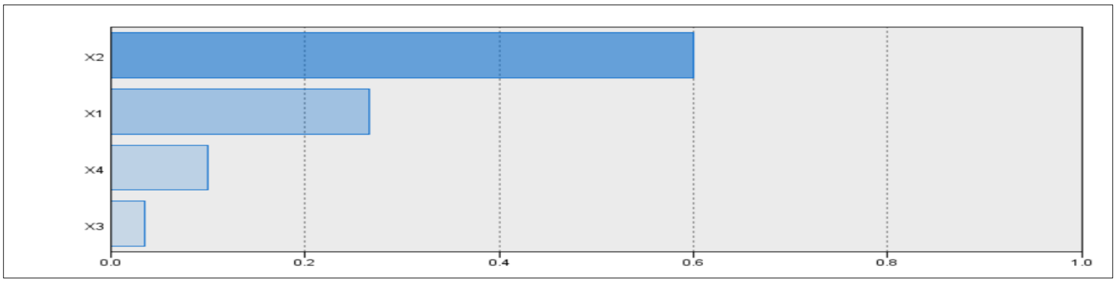

Figure 4. Results of MLPNN model
Source: authors' compilation

1. Teacher-student ratio: ($\boldsymbol{X_1}$)

Based on the empirical results shown in Table 3 and Figure 4, among the MLPNN model's training variables, the effect of the teacher-student ratio was 0.3159, which indicates a neutral correlation. One of the main reasons for this result is the low birth rate problem in Taiwan. Therefore, when the number of students decreases, it increases the number of teachers assigned to each class. We observed that the misallocation of the resources for teachers and students as well as the cost per overestimate teacher reduces the operational efficiency of schools. Therefore, when a school is not operating efficiently, it will prioritise the dismissal of teachers, which reduces costs but lowers the teacher-student ratio.

2. Total number of full-time teachers: ($\boldsymbol{X_2}$)

According to the estimated results shown in Table 3 and Figure 4. We can observe that the total number of full-time teachers of the MLPNN model training variables is 0.5994. The result of the experiment is a neutral correlation. When the school is not operating well, it will prioritise dismissing teachers. Because teachers are a fixed cost, school management costs will be down.

3. Total number of part-time teachers: ($\boldsymbol{X_3}$)

According to the estimated results shown in Table 3 and Figure 4, the effect of the total number of part-time teachers among the MLPNN model training variables was 0.0347. The empirical results do not indicate a significant correlation. When a school is not operating well, it will prioritise dismissing part-time teachers. Although part-time teachers are not a fixed cost, school management costs will be down.

4. Total number of staffs: ($\boldsymbol{X_4}$)

According to the results shown in Table 3 and Figure 4, the total number of staff among the MLPNN model training variables was 0.1. This empirical result does not indicate a significant correlation. Since staff represents a fixed cost, when a school is not operating well, it will not need a lot of staff. Thus, so when the number of students decreases, the school will lay off too many staff. However, the cost of employees was initially low, leading to a lower level of school operation and management.

We have a sufficient reason to believe that the teacher-student ratio and the total number of full-time teachers are crucial to a school's operation and management.

On the other hand, we substituted the estimated new weights in Equation (5) to calculate the range of predicted values for problem schools, which indicates whether there are problems in normal schools, thus helping to identify potential problem schools. According to the empirical results, the values for school closure ranged from 1.02 to 28.5. Thus, a predicted value below 28.5 means the school is closed.

We set the calculation of estimates along an ordinal five-point scale ranging from normal to severe and utilised different definitions based on the estimated value coefficient range results. Thus, we arranged the estimated values along a five-point ordinal scale, as presented in Table 4, which represents the increasing severity of the issue, where one is normal and five is severe.

Finally, we organised the predicted values as shown in Table 5. We found that there are a total of 19 private vocational high schools that require assistance in Taipei City, with nearly 12 schools facing a severe problem of poor management, accounting for 63% of the total, and seven schools with a predicted value below 50, which is a serious issue. These problematic schools have expressed their need for government assistance.

In contrast, we found that only four schools that are operating as normal, accounting for about 20% of the total number of schools in Taipei City. Only one school had a predicted value that exceeded 100, indicating that these four schools do not need government assistance and are not affected by the low birth rate.

Table 4. Weight value coefficient range definitions

Grading scale	Weight value	Definition
1	More than 81	Normal (0%)
2	71-80	Mild (25%)
3	51-70	Moderate (50%)
4	29-50	Moderately severe (75%)
5	Below 28.5	Severe (100%)

Source: authors' compilation

Table 5. School names and attributes

No.	School name	Predicted value	Degree of risk
1	St. Bonaventure Girls High School	30.30	Moderately severe (75%)
2	Qiang-Shu High School	30.35	Moderately severe (75%)
3	Da-Cheng High School	31.20	Moderately severe (75%)
4	Shi-Xin High School	37.40	Moderately severe (75%)
5	Ta-Tung High School	42.30	Moderately severe (75%)
6	You-De High School	42.97	Moderately severe (75%)
7	Hu-Jiang High School	51.52	Moderately severe (75%)
8	Blessed Imelda Girls High School	57.91	Moderate (50%)
9	Tai-Bei High School	59.99	Moderate (50%)
10	We-Sley Girls High School	60.20	Moderate (50%)
11	Jin-Ou Girls High School	60.48	Moderate (50%)
12	Da-Ren Girls High School	70.20	Moderate (50%)
13	Jin-Gwen High School	70.99	Mild (25%)
14	Hua-Xing High School	71.50	Mild (25%)
15	Yan-Ping High School	74.31	Mild (25%)
16	We-Go High School	83.81	Normal (0%)
17	Tsai-Hsing High School	85.30	Normal (0%)
18	Taipei Fu-Hsing Private High School	85.60	Normal (0%)
19	Dong-shan High School	100.69	Normal (0%)

Source: authors' compilation

5. CONCLUSIONS

In this study, we utilised the MLPNN model to assess the problem of school closures. We conducted a learning assessment using the MLPNN model to identify which schools have poor management and may face bankruptcy. Accordingly, we recommended prevention mechanisms that the government should pay attention to regarding schools that may meet poor management.

We found that more than half of the private schools in Taipei City may face bankruptcy. This is an indication of a serious problem. Further analysis of these findings revealed that, among the 23 schools in Taipei City, only four usually operate. The remaining 19 private vocational high schools require governmental assistance. Among these 19 schools, about 12 schools have severe cases of poor management, accounting for 63% of the total number of schools, and the other seven schools generated a predicted value below 50, which is considered a serious issue. These problematic schools have expressed their need for government assistance.

Thus, when private schools face potential bankruptcy, they typically prioritise the dismissal of full-time teachers. Since these teachers are a fixed cost, reducing the number of full-time teachers will lower school management costs; however, this will also lower the teacher-student ratio. Other factors that contribute to poor management in these schools are the reduction of staff and part-time teachers, the reduction of expenditures and the lack of operational efficiency. This leads to a vicious cycle that increases these schools' likelihood of bankruptcy.

The conclusions and recommendations presented here are based on the models constructed, sample data collected, and research methodologies employed for this study. Hence, it is necessary to consider the current situation and changes in the environment that affect the different schools in the Taiwan District, so that any application based on this study's findings can be further tailored to yield more accurate conclusions.

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