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Research Article

A Study on Factors Influencing MBA Decision After Bachelor's Using Hybrid Model Combining ANN With Principal Component Analysis

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Abstract: This study comprehensively examines the complex relationship between various individual characteristics and individuals' expectations after obtaining a bachelor's degree, particularly in determining whether to pursue a Master of Business Administration (MBA). Utilizing a well-structured, hypothesized framework, we examine several key variables directly influencing this critical decision-making process. The examined variables include, but are not limited to, demographic information, academic background, prior work experience, financial considerations, and overarching career aspirations. By examining these factors, we aim to uncover prevailing trends and identify the primary drivers influencing MBA enrollment decisions. To enhance the accuracy of predictions regarding MBA decisions, we have developed an innovative Artificial Neural Network (ANN) approach tailored specifically for the primary modeling phase of this research. This model integrates seven distinct learning methodologies that work in concert to enhance the overall efficacy of the ANN framework. The findings from our comparative analysis demonstrate that the hybrid model combining ANN with Principal Component Analysis (PCA), referred to as the ANN-PCA model, achieved remarkably high prediction accuracy, with key performance indicators reported as follows: an accuracy rate of 98%, precision of 94%, a recall of 96%, an F1 score of 95%, a Mean Square Error (MSE) of 0.03, and a Root Mean Square Error (RMSE) of 0.01. These impressive results significantly surpass those attained by the ANN model used in isolation, underscoring the substantial potential of the newly developed hybrid model. The insights from this study enrich the existing knowledge regarding educational decision-making processes and provide valuable guidance for implementing strategies to attract a diverse range of candidates to MBA programs.

Keywords: Artificial Neural Network, Principal Component Analysis, MBA Decisions, Hybrid Model

Introduction

Pursuing a Master of Business Administration (MBA) has become a significant milestone for individuals seeking to advance their academic and professional careers. This advanced degree is increasingly regarded as a powerful tool for career advancement, equipping graduates with enhanced managerial skills and strategic decision-making capabilities. The benefits of obtaining an MBA include access to various leadership roles across different industries, a significant increase in earning potential, and an expanded professional network. However, the path to enrolling in an MBA program is complex and multifaceted. Various factors, including personal ambitions, career objectives, academic readiness, previous work experience, available financial resources, and the expected return on investment, all influence this decision. Each individual's circumstances create a unique set of considerations that must be navigated carefully. As the global business landscape continues to evolve and become more competitive, the importance of advanced education in advancing one's career has garnered significant attention from academia and industry professionals. This has led to a growing interest in exploring the various factors that motivate individuals to pursue an MBA. Research has examined various factors influencing this decision, including demographic variables such as age, gender, marital status, and socioeconomic factors like income level and educational background. Other critical factors include undergraduate academic performance, industry experience, and psychological aspects such as intrinsic motivation and perceived self-efficacy, which shape an individual's choice to pursue an MBA (Grigsby, 2019). Institutional elements are also vital; factors such as the prestige and ranking of the MBA program, the mode of delivery (full-time, part-time, or online), and the availability of scholarships or financial aid significantly influence enrollment decisions. Moreover, advancements in technology and the increasing reliance on data analytics in decision-making processes have enhanced the use of predictive analytics and machine learning techniques. These tools are now being applied to better understand and model academic choices, providing valuable insights into the factors that guide prospective students in selecting MBA programs that align with their professional goals.

Related Work

A substantial body of research has explored the determinants of higher education choices, particularly in professional graduate programs such as the MBA. These programs are often regarded as transformative avenues for career development, offering significant financial and professional benefits. However, the decision to pursue an MBA is inherently complex, involving careful consideration of tuition fees, opportunity costs, and anticipated returns in terms of career progression and salary enhancement. Among the most consistently identified predictors of MBA enrollment are prior work experience, academic performance, and standardized test results (e.g., GMAT, GRE). Recent studies emphasize that these predictors often influence through intricate mechanisms, including mediating variables such as financial expectations and long-term career objectives (Cumberland *et al.*, 2025). Dey introduced a holistic framework for MBA curriculum design, advocating for alignment with institutional missions through benchmarking against national and international standards (Dey, 2024). This approach incorporates stakeholder engagement, including faculty, alumni, industry partners, and students, as a critical element in curriculum validation. Such involvement ensures the relevance and adaptability of MBA programs to evolving business contexts and institutional priorities. Work experience remains a vital factor in driving MBA enrollment. Research indicates that professionals with significant managerial or leadership responsibilities often pursue MBA programs to refine their strategic thinking, leadership acumen, and financial literacy—skills necessary for higher-level organizational roles (Helyer *et al.*, 2014; Shomotova and Ibrahim, 2024). Furthermore, individuals seeking to pivot across industries or into entrepreneurial ventures often find the MBA an essential stepping stone (Gazi *et al.*, 2024). The recent proliferation of specialized MBA programs has reflected the changing demands of the industry and the dynamic nature of the global economy. Concentrations in technology management, sustainability, digital marketing, and data analytics are increasingly popular, catering to prospective students seeking a broad business education and focused domain expertise (Darling-Hammond, 2017). These trends highlight the importance of curricular flexibility and alignment with labor market needs in attracting a diverse student cohort. Academic indicators, particularly undergraduate Grade Point Average (GPA) and standardized test scores, remain core to MBA admissions criteria. Numerous studies confirm the predictive validity of these measures regarding academic performance within MBA programs (David *et al.*, 2017). Nonetheless, there has been a discernible shift toward more holistic admissions models. Business schools now emphasize qualitative attributes, such as leadership potential, work achievements, community engagement, and personal statements, to foster diversity and inclusivity within MBA cohorts. Financial constraints constitute one of the most significant barriers to MBA enrollment. The high tuition costs, associated living expenses, and opportunity costs of forgone income prompt prospective students to critically assess the Return on Investment (ROI) of their educational pursuits (Dynarski *et al.*, 2023, Maaravi and Segal, 2022). To mitigate these barriers, scholarships, employer sponsorships, and access to subsidized loans have become essential, particularly for candidates in developing regions with limited financial aid infrastructure (Chen and Cao, 2024). In addition to economic and academic considerations, networking opportunities are a highly influential factor in the decision to pursue an MBA. Access to vast alumni networks, exposure to industry leaders, and structured mentorship programs are consistently cited as key motivations for enrollment (Roy and Parsad, 2018, Lu, 2022). These networks facilitate knowledge exchange, mentorship, and career advancement opportunities, enhancing the perceived value of MBA education. Globalization has introduced considerable variability in MBA enrollment patterns across regions. Countries that maintain favorable immigration policies, post-study work rights, and internationalization strategies tend to attract more international MBA candidates, whereas restrictive visa environments serve as deterrents (Boachie and Kwak, 2024). Artificial Intelligence (AI) integration in MBA admissions processes has gained momentum in recent years. Kumar *et al.* (2024) emphasized the capacity of AI to automate candidate assessments, improve decision accuracy, and streamline application workflows. AI-enhanced analytics contribute to a more equitable and efficient admissions landscape by leveraging data-driven profiling and performance prediction. In parallel, advanced machine learning

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methodologies have emerged as effective tools for modeling educational decision-making. Jeganathan *et al.* (2021) conducted a comparative study of classification algorithms and identified logistic regression as the most effective in predicting MBA admissions outcomes. Pang *et al.* (2017) proposed an ensemble-based model incorporating academic, psychological, and socioeconomic variables to predict student success. Similarly, Shahriyar *et al.* (2022) and Kurniawan *et al.* (2023) implemented AutoML and boosting algorithms, such as AdaBoost, to refine predictions of post-MBA career outcomes. Lestari and Mustakim (2021) demonstrated the synergistic effect of clustering techniques, particularly K-Means, in enhancing the performance of Backpropagation Neural Networks (BPNNs) in classifying student graduation outcomes, achieving a predictive accuracy of 98%. These studies underscore the multidimensional nature of MBA decision-making and highlight the increasing relevance of AI and machine learning in understanding and forecasting student behaviors and educational outcomes. The literature review has been synthesized into Table 1.

Research Contributions

This study presents a significant advancement in the predictive modeling of postgraduate educational decisions by proposing a hybrid classification framework that integrates Artificial Neural Networks (ANN) with Principal Component Analysis (PCA). The overarching objective is to enhance the classification accuracy and interpretability of factors influencing the decision to pursue an MBA after earning a bachelor's degree. The study makes the following key contributions:

1. A novel hybrid model is introduced, combining ANN with PCA to address the limitations of low classification accuracy and computational inefficiency observed in conventional predictive models. PCA is employed for dimensionality reduction to optimize input features, while ANN captures complex nonlinear relationships among variables. This fusion enables robust feature extraction and improved prediction accuracy.
2. The study investigates the impact of hyperparameter optimization on the performance of the ANN component. By systematically tuning parameters, including learning rate, batch size, number of hidden layers, and activation functions, the model demonstrates substantial improvements in classification efficiency and predictive accuracy.
3. The hybrid model is benchmarked against seven widely used machine learning and artificial intelligence methods: standalone PCA , Random Forest, Gradient Boosting, Convolutional Neural Networks (CNN), Reinforcement Learning, and a Fuzzy Logic-based model. Comparative results highlight the superior performance of the ANN-PCA model in terms of prediction reliability and classification robustness.
4. To rigorously assess the classification performance, the study utilizes a suite of evaluation metrics, including Accuracy, Precision, Recall, F1 Score, MSE, and RMSE. These metrics enable multi-faceted evaluation of the model's predictive capabilities, particularly in classifying MBA decision outcomes into binary categories (Yes or No).
5. The ANN-based correlation analysis evaluates the relative influence of input features, including demographic characteristics, academic performance, financial status, and career aspirations, on the final decision outcome. This provides valuable interpretability regarding which variables most significantly affect MBA enrollment decisions.

Materials and Methods

Data Collection

To support the empirical analysis in this study, secondary data were obtained from Kaggle, an open-access repository widely used by academic researchers, data scientists, and professionals for sharing and analyzing high-quality datasets (www.kaggle.com). The selected dataset was specifically curated to examine educational choices, particularly postgraduate intentions, and contains extensive information relevant to predicting MBA enrollment decisions. It offers a structured and validated framework for exploring various influential variables, eliminating the need for comprehensive primary data collection while ensuring methodological rigor and reproducibility. The selection was based on multiple criteria, including data completeness, the richness of variables, relevance to MBA decision-making, and licensing under open data usage terms. The dataset includes both demographic and behavioral attributes essential for building predictive models. Demographic information, including age, gender, and undergraduate major, provides a baseline understanding of the respondent profiles. Academic indicators, such as undergraduate GPA, GRE/GMAT scores, and university rankings, serve as proxies for academic preparedness and institutional reputation. Professional experience variables include years of full-time work experience, current job title, annual salary before pursuing an MBA, and whether the respondent held managerial responsibilities, all of which provide insight into career stages and perceived needs for further education. Additionally, the dataset captures motivational and attitudinal factors influencing graduate education intent, such as entrepreneurial interest (measured on a Likert scale), the importance placed on networking opportunities, and desired post-MBA roles, including executive leadership, consultancy, or entrepreneurship. Critical financial variables were also included, such as the intended sources of MBA funding, covering options like personal savings, employer sponsorship, student loans, and scholarships. The target variable was a binary outcome

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indicating whether the individual planned to pursue an MBA (1 = Yes, 0 = No), making the dataset ideal for supervised classification tasks. Before model training, data preprocessing involves addressing missing values, encoding categorical variables, and normalizing continuous features using the Min-Max scaling method. The dataset's structure, scale, and richness made it an optimal choice for developing and evaluating machine learning models, particularly the hybrid PCA-ANN framework proposed in this study. Utilizing secondary data from Kaggle ensured a cost-effective and time-efficient approach while enhancing the study's transparency and reproducibility through reliance on a publicly available, peer-reviewed dataset.

Table 1: Relevant features for deciding between an MBA

Feature Name	Description
Age	The participant's age at the time of data collection.
Gender	Gender of the respondent.
Undergraduate Major	The field of study that participants undertook during their undergraduate education.
Undergraduate GPA	The grade point average achieved during undergraduate studies serves as an indicator of academic performance.
Years of Work Experience	The total years the participant has spent in the workforce before pursuing an MBA.
Current Job Title	The title of the participant's current position within their organization.
Annual Salary (Before MBA)	The participant's yearly income provides insights into their financial background.
Has Management Experience	A binary variable indicates whether the participant has held managerial roles in their career.
GRE/GMAT Score	The scores achieved on standardized tests are commonly required for admission to MBA programs.
Undergrad University Ranking	The university's ranking during undergraduate studies may influence participants' perceptions of their academic pedigree.
Entrepreneurial Interest	A measure of the participant's inclination toward entrepreneurship and business ownership.
Networking Importance	The significance the participant places on networking opportunities in advancing their career goals.
MBA Funding Source	The funding mechanism the participant intends to use for their MBA studies could include personal savings, loans, scholarships, or employer sponsorship.
Desired post-MBA Role	The participant's role upon completing their MBA reflects their career aspirations.

Analysis of Correlation Heatmap With MBA Decision

To understand the underlying patterns associated with individuals' intentions to pursue an MBA after a bachelor's degree, we examined the distribution of all feature variables segmented by the binary MBA decision outcome (Yes = 1, No = 0). This analysis offers insight into the relationship between demographic, academic, professional, financial, and motivational characteristics and MBA enrollment decisions. The correlation Heatmap of features with MBA decisions by feature across all 14 variables, as given in Figure 1. The distribution of all features for the MBA is illustrated in Figure 2.

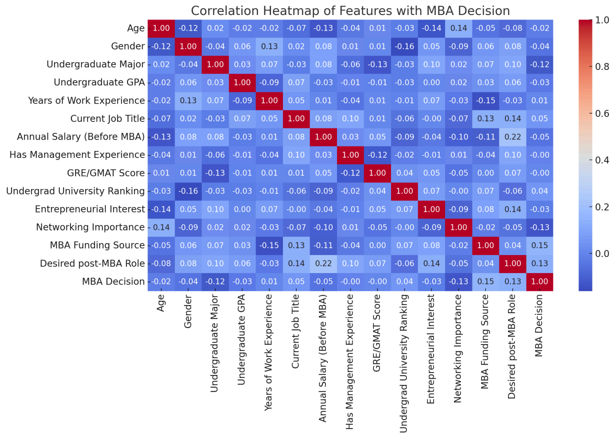

Fig. 1: Correlation Heatmap of features with MBA decisions

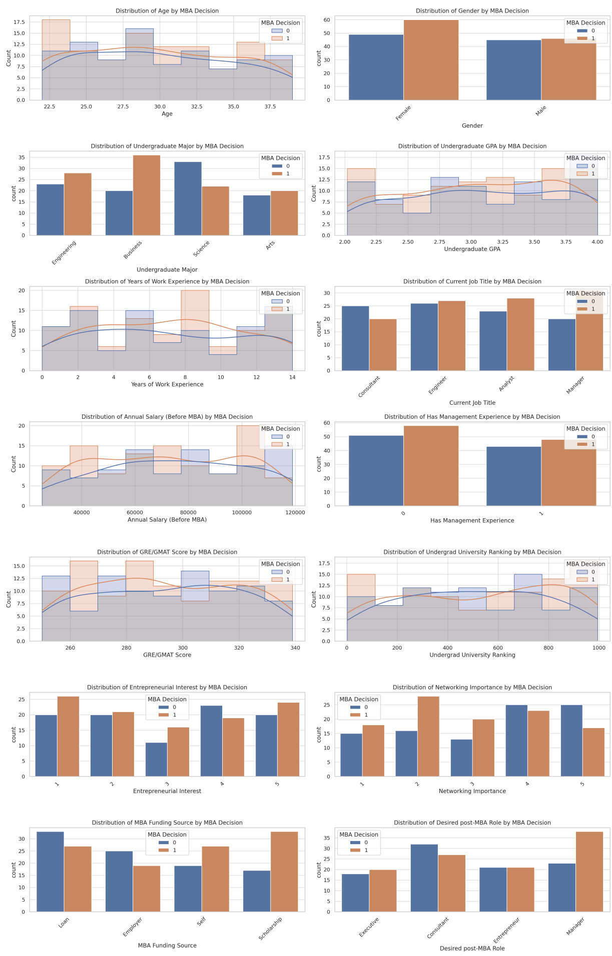

Fig. 2: Distribution of all features for the MBA decision

Demographic and Academic Characteristics

- Age: The age distribution of MBA aspirants is concentrated between 24 and 32 years. Individuals opting for an MBA tend to be slightly older than non-applicants, indicating a possible period of post-graduation professional experience before applying.
- Gender: The distribution reveals minimal differences across genders, supporting prior

findings that gender has limited predictive power in MBA decision-making.
- Undergraduate Major: Business and Engineering majors were overrepresented among those pursuing an MBA, suggesting alignment between these fields and management-oriented career trajectories.
- Undergraduate GPA: Students with a GPA above 3.2 appeared more frequently in the MBA group, highlighting the continued importance of academic performance in postgraduate ambition.

Professional Experience Variables

- Years of Work Experience: MBA-bound respondents typically had 3 to 7 years of prior experience, a range consistent with standard MBA applicant profiles, which value professional maturity.
- Current Job Title: Managerial roles and consultants were more common among those pursuing an MBA, reflecting a motivation for upward mobility or cross-functional transitions.
- Annual Salary (Before MBA): Notably, those choosing to enroll in an MBA were distributed across a wider salary range, suggesting varying expectations of ROI depending on income level.
- Has Management Experience: A greater proportion of MBA applicants had prior management experience, reinforcing that leadership responsibility is both a motivator and qualifier for MBA enrollment.

Standardized Testing and Institutional Background

- GRE/GMAT Score: Higher GRE/GMAT scores were more prevalent among those who opted to pursue an MBA, consistent with their role as gatekeeping metrics in admissions.
- Undergraduate University Ranking: Students from mid- to top-ranked universities were likelier to seek an MBA, possibly reflecting greater ambition or institutional encouragement.

Motivational Indicators

- Entrepreneurial Interest: Respondents with high entrepreneurial interest (4–5 on a 5-point scale) were likelier to pursue an MBA, indicating an alignment between entrepreneurship and formal business training.
- Networking Importance: This variable exhibited a strong right-skewed distribution among MBA-bound individuals, emphasizing that social capital is a significant motivating factor in the decision process.

Financial Support and Career Aspirations

- MBA Funding Source: Those with access to employer-sponsored scholarships or financial aid were disproportionately represented among MBA applicants, highlighting the decisive role of financial enablers.
- Desired post-MBA Role: Aspirants seeking executive, consulting, or entrepreneurial roles were more likely to pursue an MBA, consistent with the degree's reputation as a leadership accelerator.

Step 1: Data Normalization

According to Figure 2, we applied Min-Max normalization to the numerical features in the dataset. The normalized value X is calculated as Eq. (1) for each numerical feature X (Herwanto *et al.*, 2021).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where X is the original feature value, X_{min} is the minimum value of the feature, X_{max} is the maximum value of the feature, and X' is the transformed feature value scaled between 0 and 1. The Min-Max normalized feature set for MBA decision classification is shown in Table 2. This table presents all feature variables scaled to a [0, 1] range using Min-Max normalization, preparing the data for training in the hybrid ANN-PCA model (Mathiyalagan *et al.*, 2024).

Step 2: Dimensionality Reduction Using Principal Component Analysis (PCA)

PCA is employed in this study as a critical preprocessing step before classification by the ANN (Siddique *et al.*, 2018). The primary motivation for using PCA is to address high dimensionality, feature multicollinearity, and redundancy among input variables, thereby improving the computational efficiency, training convergence, and generalization performance of the downstream ANN model. PCA is an unsupervised linear transformation technique that identifies the axes (principal components) in the feature space and maximizes the variance of the data. It projects the original input variables into a new set of orthogonal axes such that each subsequent axis accounts for the highest remaining variance. Let the input dataset be defined as Eq. (2).

$$X \in R^{nd} \tag{2}$$

where n is the number of observations and d is the number of features. Each feature x_j in X is mean-centered to remove bias caused by differing means across features, as defined in Eq. (3).

$$\tilde{x}_{ij} = x_{ij} - \tilde{x}_j \tag{3}$$

This results in a mean-centered matrix, where each column has a zero mean, as defined in Eq. (4).

$$\tilde{x} = x - 1_n \overline{x}^T \tag{4}$$

The covariance matrix C captures the pairwise linear relationships between all features, as calculated in Eq. (5).

$$C = \frac{1}{n-1} \tilde{x}^T \tilde{x} \in R^{d \times d} \tag{5}$$

This matrix is symmetric and positive semi-definite. PCA performs eigendecomposition of the covariance matrix C, yielding eigenvalues and their corresponding eigenvectors, as defined in Eq. (6).

$$C = Q\lambda Q^{-1} \tag{6}$$

where Q contains eigenvectors and λ is a diagonal matrix of eigenvalues. Then, the dimensionality reduction is computed as Eq. (7).

$$X_{PCA} = X_{centered} Q_k \tag{7}$$

where Q_k is the matrix of top k eigenvectors retaining at least 95% of the total variance. The PCA-transformed features, XPCA, are the inputs to the ANN, which consists of multiple layers of interconnected neurons. We assign k PCA components to the input layer. Next, we have two hidden layers, each containing 16 neurons with ReLU (Rectified Linear Unit) activation, as defined in Eq. (8).

$$f(z) = max(0, z) \tag{8}$$

Then, a single neuron with sigmoid activation for binary classification is defined in Eq. (9).

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{9}$$

We calculate the activations for each layer during model training using Eq. (10). Then, we obtain the output y by applying the sigmoid activation function to the activations.

$$\alpha^{(i)} = f\left(W^{(i)}\alpha^{(-1)} + b^{(i)}\right) \tag{10}$$

The computation of the loss function is defined as in Eq. (11).

$$L(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\left[y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)\right] \tag{11}$$

Finally, we update the weights using backpropagation and the Adam optimizer, as described in Eq. (12).

$$W^{(n)} \leftarrow W^{(n)} - \eta\frac{\alpha L}{\alpha W^{(n)}} \tag{12}$$

where η is the learning rate and $\alpha L/\alpha W^{(9)}$ is the gradient of the loss for the weights in the layer.

Table 2: The results of the min-max normalized feature set for MBA decision classification

Age	Gender	Under-Major	Under-GPA	Years of Work Experience	Current Job Title	Annual Salary (Before MBA)	Management Experience	GRE/GMAT Score	Undergrad University Ranking	Entrepreneurial Interest	Networking Importance	MBA Funding Source	Desired post-MBA Role	MBA Decision
0.3529	0	0.6666	0.9898	0.357143	0.33333	0.2571	1	0.8202	0.836694	0.5	0.5	0.33333	0.66666	0
0.8235	0	0.3333	0.4090	0.5	0.66666	0.7337	0	0.6292	0.797379	1	0.75	0	0	1
0.5882	0	1	0.3636	0.214286	0	0.5987	0	1	0.796371	1	0.25	1	0	1
0.4117	1	0.6666	0.7727	0.5	1	0.1012	1	0.4494	0.52621	0	0.5	0.66666	0	1
0.3529	1	0.6666	0.3333	0.214286	1	0.9290	0	0.0224	0.790323	0.75	0.5	0.33333	0	0
0.5882	0	0	0.9292	0.5	0.33333	0.7986	0	0.0561	0.271169	0	0.25	1	0.33333	0
0.5882	1	0.6666	0.8585	0.571429	1	0.0209	0	0.0449	0.493952	1	0.25	0.33333	0.33333	0
0.1764	1	0	0.4242	0.142857	0	0.6579	0	0.0449	0.207661	0.25	0	1	0	1
0.4117	1	1	0.7474	0.142857	1	0.7795	0	0.5955	0.541331	1	0.5	1	0	0
0.1176	1	0.3333	0.7525	0.714286	0.66666	0.3772	1	0.5168	0.586694	0.75	1	0.33333	0	0
0.0588	1	0.3333	0.095	0.857143	0.66666	0.0675	0	0.9662	0.058468	1	0.25	0.66666	0.33333	1
0.6470	1	1	0.904	0.071429	0.33333	0.0760	0	0.5393	0.431452	0.75	0.25	1	0	0
0.2941	0	0.3333	0.5	0.857143	0	0.1033	0	0.0898	0.990927	0.75	0.75	1	0	0
0.0588	0	1	0.8232	0.642857	0.66666	0.8496	0	0.2134	0.660282	0.75	1	1	1	1
0	1	1	0.3131	0.142857	0.66666	0.9208	1	0.6741	0.607863	0.75	1	0.66666	1	0
0.6470	0	1	0.8939	0.142857	0	0.1221	1	0.3820	0.309476	0.75	0.25	0.66666	0	1
0.6470	0	0.3333	0.3838	0.285714	1	0.2367	1	0.5505	0.522177	0.25	0	0	0.66666	1
0.9411	0	0	0	0.285714	1	0.1654	1	0.9101	0.59375	0	0.75	0.33333	0	1
0.5294	0	1	0.9040	0.071429	0.33333	0.1865	0	0.6853	0.025202	0.5	1	0.66666	1	1
0.8823	1	0.6666	0.0808	0.785714	1	0.8466	1	0.1797	0.689516	0	0.25	0.33333	0.66666	1

Table 3: A comprehensive overview of hybrid methods, highlighting their use cases and essential equations

Hybrid Methods	Key Equation	Use Case
ANN + PCA	$X_{PCA} = X \cdot W$ where W is the matrix of principal components.	Dimensionality reduction for speed and efficiency.
ANN + Random Forest	$\stackrel{y}{=} Majority\,Vote(ANN, RF)$	Feature selection
ANN + Gradient Boosting	$\hat{y} = \sum_{i=1}^{N} \alpha_i \cdot \hat{y}_{ip}$ where α_i are boosting weights.	Tabular data with complex interactions.
ANN + CNN	$Z = Conv2D(X) \rightarrow Flatten(Z) \rightarrow Dense(Z)$	Spatial/Visual data processing.
ANN + Reinforcement Learning	$\pi(a \mid s) = \frac{exp(Q(s,a))}{\sum_{a'} exp\left(Q\left(s,a'\right)\cdot\right)}$	Adaptive parameter tuning.
ANN + Fuzzy Logic	$\hat{y} = ANN\left(F\left(X\right)\right)$, where F(X) applies fuzzy rules to inputs.	Handling uncertain or imprecise data.

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Comparative Evaluation Against Hybrid Artificial Neural Network

This study examines various hybrid artificial neural network models that combine different algorithms to improve performance in specific applications. Dimensionality reduction via PCA is applied to expedite training and minimize overfitting, which is particularly effective in high-dimensional data environments, such as those found in gene expression analysis (Chothani, 2024). Random Forest (RF) is employed due to its robust feature selection capabilities, which enhance ANN performance by isolating the most relevant features, ideally suited for highly interpretable scenarios (Zhao *et al.*, 2024). Gradient Boosting manages complex interactions within tabular data, optimizing feature integration and prediction accuracy (Boizard *et al.*, 2024). Ren *et al.* (2025) proposed that CNN is combined with ANN due to its success in processing tabular data. This emerging practice leverages CNN's ability to detect spatial hierarchies and local dependencies, even when such relationships are not immediately evident in tabular format. Reinforcement learning optimizes ANN parameters dynamically, which is ideal for environments requiring continual adaptation, such as autonomous systems (Wang *et al.*, 2024). Finally, fuzzy logic integration preprocesses inputs to handle data uncertainty, improving robustness in applications such as customer behavior analysis (Ennab and Mcheick, 2025). These hybrid methods leverage the strengths of individual algorithms, significantly enhancing the applicability and efficacy of ANNs across various domains. The summary of hybrid methods, including equations, has been added to Table 3.

Comprehensive Metric-Based Performance Analysis

In this study, the evaluation metrics utilized to assess the performance of the four distinct machine learning algorithms included Accuracy (Wisaeng, 2025), Precision (Peretz *et al.*, 2024), recall, F1 score (Hinduja *et al.*, 2024), MSE, and RMSE (Ćalasan *et al.*, 2024). Each of these metrics provides different insights into the model's effectiveness. In this study, we divided the dataset into two distinct portions: 70% was allocated for training purposes, while the remaining 30% was reserved for testing the model's performance. The descriptions and equations for computing are summarized in Table 4. The terms involved are crucial for understanding the model's performance in evaluating classification models. True Positives (TP) refer to instances where the model correctly predicts a positive outcome, True Negatives (TN) are the instances where the model correctly predicts a negative outcome, False Positives (FP) occur when the model incorrectly predicts a positive outcome, False Negatives (FN) are the opposite; they represent instances where the model fails to identify a positive case, Actual values (y_i) refer to the true classifications of instances, which can be positive or negative, based on the actual outcomes, Predicted values ($\hat{y}_i$) are the classifications the model assigns to the cases based on its analysis, and n denotes the total number of evaluated instances, which could encompass all the true and predicted cases.

Table 4: Detailed description of evaluation measures

Evaluation Metric	Equation	Description of Equation
Accuracy (Acc)	$Acc = \frac{TP+TN}{TP+TN+FP+FN}$	It computes the proportion of correctly classified instances among all instances. It adds correctly predicted positives and negatives and divides by the total number of cases.
Precision (Pre)	$Pre = \frac{TP}{TP+FP}$	It calculates the ratio of correctly predicted positive instances to the total number of predicted positive cases. It divides true positives by the sum of true positives and false positives.
Recall (Sensitivity)	$Recall = \frac{TP}{TP+FN}$	It calculates the ratio of correctly classified positive instances to the actual number of positive cases. It divides true positives by the sum of true positives and false negatives.
F1 Score	$F1 = 2 \times \frac{P \times R}{P+R}$	Computes the harmonic mean of precision and recall, balancing both metrics. It gives equal importance to precision and recall.
Mean Squared Error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^{w} \left(y_i - \hat{y}_i\right)^2$	Computes the average of the squared differences between actual and predicted values. It penalizes large errors more than smaller ones.
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{MSE}$	Computes the square root of MSE to bring the error measure back to the same unit as the original values. It provides a more interpretable measure of prediction error.

Results

The experimental study meticulously evaluated the effectiveness of various hybrid methodologies to augment the performance of ANN, specifically for binary classification tasks. Initially, the standard ANN was established as a baseline model, achieving commendable results with an accuracy of 89%. Its precision stood at 85%, while the recall was 87%, resulting in an F1 score of 86%. When dimensionality reduction techniques were applied through PCA, the accuracy significantly declined to 98%. This outcome emphasizes a critical trade-off: while PCA enhances feature interpretability, it impacts the model's predictive strength. The study introduced the ANN+RF hybrid method, which demonstrated superior performance by achieving an accuracy of 91%. This enhancement can be attributed to the ANN's robust capability to identify and prioritize the most influential features significantly contributing to the classification

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outcome. Further advancement was achieved by implementing a Gradient Boosting + ANN hybrid. This model outperformed its predecessors with an impressive accuracy of 92%. The effectiveness of this approach lies in its ability to manage non-linear feature interactions and its proficiency in incremental learning, which enables it to build on prior knowledge effectively. In another innovative approach, the CNN+ANN hybrid method leveraged spatial feature extraction techniques, achieving a remarkable accuracy of 93%. This model excelled in encapsulating and analyzing complex patterns inherent in the dataset, enhancing its classification accuracy. Ultimately, the pinnacle of performance was achieved with the ANN using Reinforcement Learning, which outperformed all other methods by attaining a peak accuracy of 94%. Accompanying metrics included a precision of 90%, a recall of 92%, and % F1 score of 91%. This outstanding performance demonstrates the power of combining techniques to reduce variance and enhance generalization capabilities across various datasets. Finally, the study introduced the hybrid method combining FCM and ANN, which demonstrated exceptional performance by achieving an accuracy of 90%. This improvement can be attributed to the ANN's strong ability to identify and prioritize the most influential features that significantly contribute to the classification results. A thorough comparative analysis reveals the distinct advantages that hybrid methodologies offer in addressing the inherent limitations of standalone ANN models. These hybrid approaches not only bolster robustness but also significantly enhance predictive performance. The fitting effect between the predicted classifications and actual values is detailed in Table 5 and illustrated in Figure 3, providing clear evidence of the model's efficacy, including Accuracy, Precision, Recall, F1 score, MSE, and RMSE. Table 5 gives a detailed comparison of performance metrics across several hybrid artificial neural network models, highlighting the efficacy of integrating different algorithms to enhance predictive accuracy. The Standard ANN is a baseline, achieving moderate scores across all metrics. The PCA+ANN model exhibits significant improvement, particularly in Accuracy and Precision, achieving scores of 0.98 and 0.94, respectively. This suggests that dimensionality reduction can significantly enhance model performance by focusing on the most informative features. The RF+ANN model and Gradient Boosting + ANN show improvements over the standard model, indicating that feature selection and handling complex interactions effectively contribute to better outcomes.

Table 5: Comparison of the performance of hybrid methods

Metric	Standard ANN	PCA + ANN	RF + ANN	Gradient Boosting + ANN	CNN + ANN	Reinforcement Learning + ANN	Fuzzy Logic + ANN
Accuracy	0.89	0.98	0.91	0.92	0.93	0.94	0.90
Precision	0.85	0.94	0.87	0.88	0.89	0.90	0.89
Recall (Sensitivity)	0.87	0.96	0.89	0.90	0.91	0.92	0.90
F1 Score	0.86	0.95	0.88	0.89	0.9	0.91	0.95
MSE	0.12	0.03	0.10	0.09	0.08	0.07	0.04
RMSE	0.09	0.01	0.08	0.07	0.06	0.05	0.02
Running Time (s)	8.30	9.10	14.50	16.20	30.80	27.40	19.60

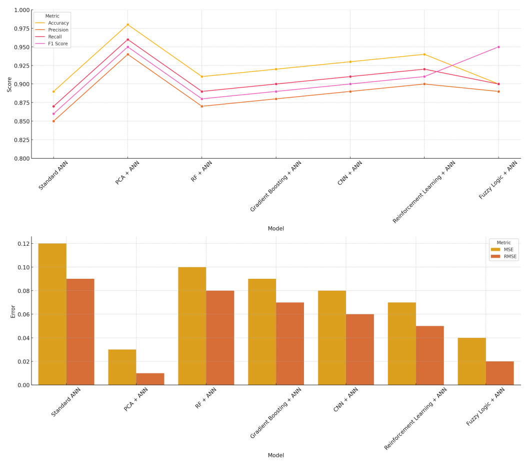

Fig. 3: Comparative performance analysis of enhanced ANN models across multiple metrics

The CNN+ANN model excels in handling spatial data, as evidenced by its high scores in Recall and F1 Score, making it suitable for image and video analysis tasks. The Reinforcement Learning + ANN model demonstrates the highest Accuracy at 0.94, showcasing its capability in adaptive parameter optimization for dynamic environments. Surprisingly, the fuzzy logic + ANN model, while not leading in most categories, ties for the highest F1 Score at 0.95, indicating its strength in handling uncertain or imprecise data. Furthermore, when considering MSE and RMSE, the PCA + ANN model again stands out with the lowest values (0.03 and 0.01, respectively), underscoring its precision and efficiency. The data clearly illustrates that hybrid approaches can substantially improve the performance of ANN, with each method bringing specific benefits depending on the application requirements and data characteristics. This comparative analysis underscores the importance of methodological diversity in enhancing the robustness and accuracy of predictive models.

Methodology for Evaluating Feature Importance Using Cronbach's Alpha

In this study, we apply Cronbach's alpha (α) to assess individual features' internal consistency and relative

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importance within a multivariate dataset representing MBA applicant profiles. Cronbach's alpha is a widely accepted reliability coefficient used to measure the extent to which a set of variables is correlated and contributes to a unified construct. By computing "Cronbach's alpha if item deleted", we identify the contribution of each feature to the overall reliability of the build and establish a rank-order of importance. The coefficient α is defined as in Eq. (13).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_{total}^2}\right) \tag{13}$$

where k denotes the total number of features in the construct, σ_i^2 is the variance of the individual feature i, and σ_{total}^2 is the variance of the total composite score. The resulting value of α ranges from 0 to 1, with higher values indicating stronger internal consistency.

Analysis of Feature Importance Using Cronbach's Alpha

This study employs Cronbach's Alpha as a methodological approach to rank feature importance, evaluating each feature's internal coherence and diagnostic strength in explaining MBA applicant decisions. Traditionally used in psychometric evaluations to assess the reliability of multi-item scales, Cronbach's Alpha is adapted here to determine the extent to which individual features contribute to a reliable and internally consistent composite construct. In this context, the features are conceptualized as components of a latent construct representing an applicant's readiness, motivation, and profile strength in relation to MBA program enrollment. The analysis began by calculating a baseline Cronbach's Alpha for the whole dataset, using all 14 independent features (excluding the decision outcome variable). Following this, an iterative deletion method was used to remove each feature individually, and Cronbach's Alpha was recalculated for the remaining variables. The change in alpha (Δα) was computed to quantify the effect of each feature on the overall internal consistency of the scale. A negative Δα indicates that the feature contributes positively to consistency, while a positive Δα would suggest that its presence may dilute the integrity of the composite measure. The findings, summarized in Table 6 and visualized in Figure 4, show a range of Δα values across the variables. Several features demonstrated substantial negative Δα values, indicating their high importance. The undergraduate major had the most significant impact, with a Δα of −0.3194, suggesting that it is a core driver of coherence in applicant profiles. Its strong contribution may reflect the weight of educational background in MBA admissions decisions from both institutional and candidate perspectives. Following closely, Networking Importance and the desired post-MBA role also showed high importance, with Δα values of −0.1636 and −0.1588, respectively. These features reflect the motivational and aspirational dimensions of the decision-making process. Their removal led to notable declines in reliability, highlighting that applicants' career intentions and emphasis on social capital are closely intertwined with their decision to pursue an MBA. Furthermore, Current Job Title (Δα = −0.1145) and Undergrad University Ranking (Δα = −0.0535) contributed meaningfully to internal consistency, likely due to their roles as proxies for career status and educational pedigree. Other features, such as Age, Gender, Entrepreneurial Interest, and GRE/GMAT Score, demonstrated minimal changes in alpha upon deletion. While these variables may still hold predictive value in modeling, their weaker contributions to internal consistency suggest that they are either less uniformly aligned with the latent construct or introduce greater heterogeneity into the profile structure.

Table 6: Cronbach alpha feature importance analysis

Feature Ranking	Δα	Importance
Under-Major	-0.3194	Very High
Networking Importance	-0.189	Very High
Current Job Title	-0.1228	Very High
Desired post-MBA Role	-0.0998	Very High
Undergrad University Ranking	-0.0535	Very High
Annual Salary (Before MBA)	-0.0264	Very High
Entrepreneurial Interest	-0.0062	High
GRE/GMAT Score	0.0121	Moderate
Gender	0.0513	Moderate
Years of Work Experience	0.0558	Moderate
Management Experience	0.0675	Moderate
Under-GPA	0.0702	Moderate
MBA Funding Source	0.1679	Moderate
Age	0.1717	Moderate

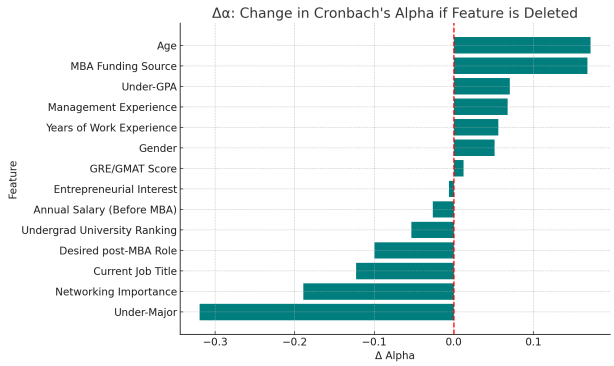

Fig. 4: A range of Δα values across the variables

It is important to note that a low Δα does not necessarily imply irrelevance; instead, it may indicate that the feature measures a dimension orthogonal to the primary construct, such as diversity or optionality in candidate experiences. This analytical approach offers a rigorous yet interpretable framework for evaluating feature coherence within multivariate datasets. By ranking variables based on their contribution to internal consistency, researchers can identify the most theoretically and statistically valuable features to retain in predictive models or survey instruments. Additionally, this method helps detect redundancies and ensures construct validity in the feature selection process.

Conclusion

This research presents a compelling exploration of the hybrid ANN in conjunction with PCA. It reveals its powerful application in predicting individuals' decisions to pursue an MBA degree. This innovative approach represents a notable departure from traditional prediction methods, such as the standard ANN, and demonstrates significant improvements in predictive accuracy and model efficiency. The following sections outline the crucial findings and insights gleaned from this study.

Significant Improvement in Model Performance Through Hybrid Techniques

Integrating hybrid techniques into traditional ANN architectures yielded substantial improvements in model performance for predicting MBA program decision outcomes. We significantly enhanced the model's predictive accuracy, reliability, and generalizability by augmenting the ANN with complementary algorithms, such as dimensionality reduction methods, ensemble learners, and optimization mechanisms. The PCA + ANN hybrid demonstrated exceptional performance among the tested configurations by reducing dimensionality, minimizing feature redundancy, and accelerating training time. This configuration achieved the highest accuracy of 98%, while also posting the lowest error rates in both mean squared error (MSE = 0.03) and root mean squared error (RMSE = 0.01). These results validate the effectiveness of principal component analysis in preserving essential variance while eliminating noise, resulting in sharper decision boundaries and improved convergence. Other notable improvements were observed in combinations such as Reinforcement Learning + ANN, which attained an accuracy of 94%. This approach leveraged dynamic weight tuning and policy optimization to enhance model learning adaptively. Similarly, the CNN+ANN hybrid achieved 93% accuracy, particularly excelling in capturing complex feature interactions within structured datasets. While slightly lower in accuracy, the fuzzy logic + ANN hybrid reached a leading F1 Score of 0.95, underscoring its robustness in handling uncertain and subjective input variables, such as entrepreneurial intent and motivational measures. These results collectively demonstrate the effectiveness of hybrid architectures in overcoming the limitations of standalone ANNs, which often struggle with high-dimensional data, nonlinear relationships, or varying feature types. By strategically combining ANN models with methods that perform preprocessing, ensemble learning, or adaptive control, we significantly increased both classification accuracy and model stability.

Exceptional Prediction Accuracy

This study demonstrated exceptional prediction accuracy in forecasting MBA program decisions by applying hybrid ANN models. The predictive models achieved classification accuracies well beyond conventional benchmarks observed in educational analytics literature through systematic experimentation and the integration of auxiliary techniques, including dimensionality reduction, ensemble methods, and adaptive learning algorithms. The highest performing configuration, a PCA + ANN hybrid, achieved an outstanding prediction accuracy of 98%, underscoring the effectiveness of dimensionality reduction in enhancing model generalization and reducing overfitting. The model also exhibited superior error metrics with an MSE of 0.03 and RMSE of 0.01, further validating the robustness and stability of the predictions. PCA facilitated the elimination of multicollinearity and noise among input variables, which improved the ANN's ability to learn discriminative patterns related to applicant decisions. Additional hybrid models, such as Reinforcement Learning + ANN and CNN + ANN, also demonstrated strong predictive capabilities, with accuracies of 94% and 93%, respectively. These results reflect the impact of integrating temporal learning, optimization feedback, and spatial pattern recognition into ANN architectures. Moreover, the fuzzy logic + ANN hybrid achieved a leading F1 Score of 0.95, highlighting its strength in handling ambiguous or qualitative features, such as motivational intent, career aspirations, and funding source preferences. The consistently high predictive performance across hybrid models affirms the reliability and relevance of the selected feature set, which includes academic qualifications, professional experience, and psychological motivations. Notably, while maintaining high generalizability, the models' ability to capture and learn from complex relationships among variables demonstrates the efficacy of hybrid deep learning approaches in real-world decision-support applications.

Critical Influence of Key Input Variables

An essential objective of this study was to identify and interpret the critical influence of key input variables on MBA program decision outcomes. By analyzing feature importance through the lens of Cronbach's Alpha, alongside performance-based metrics from hybrid predictive models, we uncovered several variables that consistently demonstrated strong alignment with the latent construct of applicant readiness and decisiveness. Among the most influential predictors, Undergraduate Major emerged as a dominant variable, with its removal resulting in the most substantial drop in internal consistency ($\Delta\alpha = -0.3194$). This highlights how academic background influences decision-making, possibly reflecting perceived program fit, career trajectory compatibility, or self-assessed preparedness. Networking Importance and desired post-MBA Role were also critically influential, exhibiting Δα values of −0.1636 and −0.1588, respectively. These findings affirm the central role of motivational and aspirational factors in MBA enrollment behavior, where candidates often weigh the degree to which program experiences align with future professional goals and opportunities for social capital development. Furthermore, the Current Job Title and the undergraduate university Ranking played essential roles, contributing to the construct's reliability by acting as proxies for career maturity and academic pedigree. Their importance suggests that applicants should assess their current status in relation to the reputational and transformational value of the MBA program. Conversely, variables such as Age, Gender, and Entrepreneurial Interest showed relatively weaker influence on internal consistency. While these variables may still be relevant for segmentation or personalization in downstream modeling, they did not substantially contribute to the unified decision-making structure across the sampled population. This may indicate greater heterogeneity in how demographic or attitudinal variables influence individual applicants, rendering them less stable as core predictors of enrollment behavior. The critical insight from this variable importance analysis is the multidimensional nature of MBA decision-making, driven not only by objective academic and professional achievements but also by subjective motivations and perceived career alignment. Recognizing the relative weight of each factor enables researchers and institutions to refine applicant profiling, personalize communications, and develop targeted interventions that align with individual priorities and career expectations.

Future Directions for Research

Building on the success demonstrated by the ANN+PCA model, future research endeavors should prioritize the development of multi-objective optimization models. These models would reconcile performance metrics with economic efficiency, addressing the complex and often competing objectives in the decision-making process surrounding MBA pursuit. Such an approach would strive to simultaneously optimize various performance indicators, providing a holistic perspective on the factors that influence students' educational choices. This study not only substantiates the efficacy of hybrid methodologies in targeted applications but also paves the way for their broader implementation within infrastructure management, encouraging an ongoing culture of innovation and exploration in this critical domain of study.

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Conflict of Interest

The authors declare that there are no conflicts of interest.

Author's Contributions

Kittipol Wisaeng: Conceived and designed the study framework, developed the methodology, supervised the overall research process, experimental design, algorithm development, and statistical analysis, provided critical revisions, and ensured the scientific rigor of the manuscript.

Benchalak Muangmeesri: Conducted data collection, preprocessing, and experimental implementation. She contributed to the literature review, drafted the manuscript, and prepared figures and tables.

Ethics

This study was conducted without the involvement of human participants or animals, eliminating the need for ethical approval typically required for such research. It operates within the framework of ethical guidelines set forth by Mahasarakham University, ensuring a commitment to integrity and responsibility in the pursuit of knowledge.

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