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Machine Learning Predictive Models for Faculty Selection and Promotion in Public Higher Education Institutions in the Philippines

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Abstract: This research investigates the efficacy of predictive models, specifically Logistic Regression, in the context of faculty selection and promotion within Public Higher Education Institutions (PHEIs) in the Philippines. With the ever-growing demands on academic institutions to guarantee the excellence and significance of their faculty, the study aims to develop a robust framework that leverages predictive analytics to enhance management processes. The research methodology includes the collection and study of comprehensive data sets encompassing academic qualifications, teaching experience, research contributions, and other relevant factors for faculty members. The Logistic Regression model is employed to discern patterns and relationships within these data, providing a systematic approach to evaluating faculty performance and potential. The model's predictive capabilities are then assessed through comparisons with historical promotion outcomes. Performance metrics such as accuracy, precision, and recall are employed to evaluate the predictive capabilities of the models. Results indicate that the logistic regression models exhibit promising accuracy rates and effectively identify candidates for selection and promotion with an accuracy of 80% (accurate), precision of 79% (precise), and recall or sensitivity of 89% (highly sensitive). The study underscores the significance of predictive analytics in informing strategic decision-making processes within educational institutions and highlights the potential for enhancing faculty recruitment and advancement practices.

Keywords: *Faculty Promotion, Faculty Selection, Higher Education, Logistic Regression, Machine Learning Algorithms, Predictive Models*

1. Introduction

Analytics for human resources (HR) are becoming more and more popular in HR management since they can quickly and effectively evaluate personal data to improve decision-making. HR uses personnel acquisition (TA), a strategic process, to determine the long-term manpower needs for organizational goals. As a result, HR analytics uses data analysis to make informed decisions and find talent. [1].

Data analytics has become more important in human resource management (HRM) due to its capacity to deliver insights based on data-driven decision-making processes. However, integrating an analytics-based strategy in human resource management is a complicated process, therefore many firms are unable to embrace HR Analytics (HRA) [2].

Recruitment may be described as a company's technique for identifying potential applicants to fill existing or anticipated openings. Typically, there is a push to pick up the excitement of the up-and-comers looking for jobs, find the up-and-comers keen on the activity and organize a meeting of possible representatives, with the help of which the administration can select the most appropriate person for the task [3].

Recruitment and selection are among the most common activities in the human resources field. Organizations are progressively reinventing themselves and upgrading their strategies in response to technological advances [4]. The efficient use of artificial intelligence can enhance recruitment techniques [5]. Artificial intelligence can help in the analysis of candidate responses [6].

Faculty promotion is vital for retention and innovation [7]. Faculty selection should involve a comprehensive evaluation of applicant applications. The comprehensive evaluation highlights the need to assess the institution's values [8][9][10].

Favoritism in recruitment and selection is a chronic concern in countries where the consequences of globalization are becoming more pronounced. Because of the increasing professionalism of local workplaces, management in these cultures is now frequently required to base recruiting choices solely on individuals' credentials and merit [11][12].

Recruitment includes not just employing the most qualified candidates, but also satisfying other corporate goals. For example, there is a need to fulfil the need for staff in various departments, to facilitate team diversity, and to allocate the workforce in an equitable way [13].

Recruitment and selection had most likely benefitted the most from the advancement of technology solutions over the previous several decades. The first research on the significance of e-hr surfaced in the early 2000s, forecasting

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the positive influence of technology across many HR tasks [14][15].

The focus of this research is the creation and application of predictive analytics models to enhance and streamline the procedures of faculty recruitment and progression within the framework of public higher education in the Philippines.

This study aims to construct predictive models specifically designed for evaluating the appropriateness of potential faculty candidates and predicting the probability of successful promotions for current faculty members. The variables that are considered significant in the academic arena are diverse and involve a wide range of characteristics. These factors include academic accomplishments, teaching effectiveness, research output, and other relevant elements. By considering these many variables, a more nuanced comprehension of the components that contribute to success in academia may be achieved.

This extensive investigation aims to provide significant insights that might assist decision-makers in public higher education institutions in the Philippines. Using predictive analytics, this research seeks to provide a valuable contribution to the improvement and optimization of faculty management, eventually resulting in the enhancement of the overall quality and efficacy of academic institutions within the nation.

1.1. Objectives

The objectives of this study aim

(1) To design and develop predictive analytics models tailored for evaluating the suitability of faculty candidates and forecasting the potential success of existing faculty members in the context of Philippine public higher education; and

(2) To evaluate the performance and accuracy of the developed predictive analytics models through testing and validation processes, ensuring their reliability in predicting faculty success.

2. RELATED LITERATURE

2.1. Public Higher Education Institutions Faculty Rank

Public Higher Educational Institutions adhere rigorously to the concepts of merit, physical fitness, and equality. The selection of personnel shall be based on their relative qualifications and capacity to carry out the position's duties and obligations. In accordance with recognized ethical norms, there shall be no discrimination in the selection of personnel based on religion, ethnicity, impairment, political affiliation, civil status, or gender [16][17].

Table 1. Faculty Positions

Rank	***Sub-Rank***
Instructor	Instructor I
	Instructor II
	Instructor III
Assistant Professor	Assistant Professor I
	Assistant Professor II
	Assistant Professor III
	Assistant Professor IV
Associate Professor	Associate Professor I
	Associate Professor II
	Associate Professor III
	Associate Professor IV
	Associate Professor V
Professor	Professor I
	Professor II
	Professor III
	Professor IV
	Professor V
	Professor VI
	College/University Professor

Table 1 specifies the different ranks of faculty from Instructor to Professor and their corresponding sub-ranks. The highest plantilla/sub-rank position for Local Universities and Colleges is Associate Professor V.

2.2. Machine Learning

The scientific study of statistical models and methods used by computer systems to accomplish tasks is known as machine learning, or ML. Learning algorithms are used by many of the systems we use on a regular basis. One of the reasons a search engine like Google performs so well when used to search the internet is because it ranks websites using a learning algorithm. These algorithms are used for many different tasks, such as image processing, predictive analytics, and data mining. The main advantage of using machine learning is that algorithms can work automatically once they know what to do with the data [18]. Machine learning algorithms often ingest and process data to discover patterns regarding persons, corporate processes, transactions, occurrences, and so on [19].

Machine Learning (ML) has transformed the computing industry by enabling computers to acquire knowledge as they go from massive datasets, eliminating many of the traps and dead ends of earlier programming. When exposed to massive amounts of information, machine learning algorithms may self-teach and grow [20].

A specialized expert supervises the learning process in supervised machine learning (SML), a subfield of machine learning, and together they create a task that maps inputs to desired outputs. In characterization tasks, this approach is commonly used to familiarize computers with produced descriptive frameworks. [21].

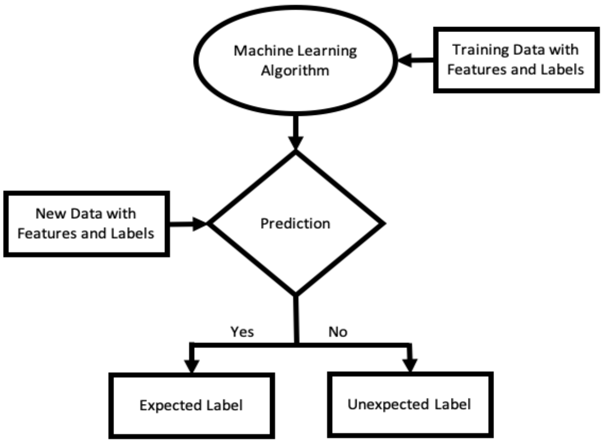

Fig. 1. Supervised Machine Learning [22]

3. Methodology

3.1. Research Framework

Prior to defining the solutions, it is necessary to construct a research framework. Based on previous research [23], this methodology is modified to construct predictive models from the collection of data to evaluation. The framework for investigation is illustrated in Figure 2. Data preprocessing, model construction, model evaluation, and data acquisition are the four primary processes that comprise this research project.

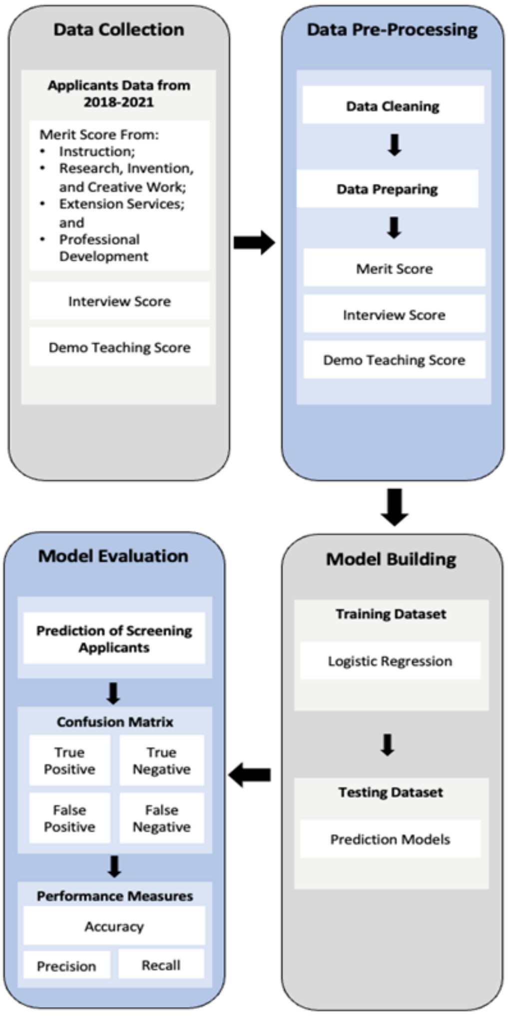

Fig. 2. Adapted Research Framework [23]

Data Collection: Applicants' information was gathered following the research framework from 2018 to 2021. Interview scores, teaching demonstrations, merit scores derived from instruction, research, invention and creative works, extension services, and professional development were among the metrics included in the dataset. The comprehensive dataset offered a thorough synopsis of the credentials and accomplishments of the applicants throughout the designated timeframe.

Data Pre-Processing: Thorough data cleansing and preparation procedures were implemented on the gathered data. In addition to addressing missing values and outliers, measures were taken to ensure the overall quality of the dataset. To prepare the data for subsequent analyses, categorical variables were encoded, numerical features were scaled, and any other required transformations were implemented.

Model Building: During the model construction phase, the produced dataset was utilized to train a logistic regression model. Logistic regression was selected as an appropriate approach for binary classification tasks on account of its ability to represent the likelihood of a binary result using predictor variables as input. Furthermore, prediction models were constructed and evaluated for effectiveness using an independent dataset.

Model Evaluation: The practical application of models to predict candidates' screening outcomes marked the evaluation phase. Assessing the model's performance involved a detailed examination using a confusion matrix, which categorized instances into false positives, false negatives, true positives, and true negatives. Performance measures such as accuracy, precision, and recall were utilized to quantitatively assess the models' effectiveness in screening applicants. These metrics provided valuable insights into the overall accuracy of predictions, the specificity of positive predictions, and the proportion of accurate positive identifications relative to all true positives. Through this comprehensive evaluation process, a deep understanding of the predictive capabilities of the developed models in applicant screening was achieved.

3.2. Model Algorithm

Logistic regression, an extension of the linear model, relaxes fundamental linear assumptions. It effectively models relationships with non-continuously measured outcomes, unlike linear regression, which requires continuous scale data. This technique is commonly employed in classifying data into distinct categories, termed classification. Classification scenarios include binomial (e.g., active/inactive, promoted/not promoted), multinomial (e.g., job family, location), or ordinal (e.g., Likert scale survey items, performance level, education level). [24].

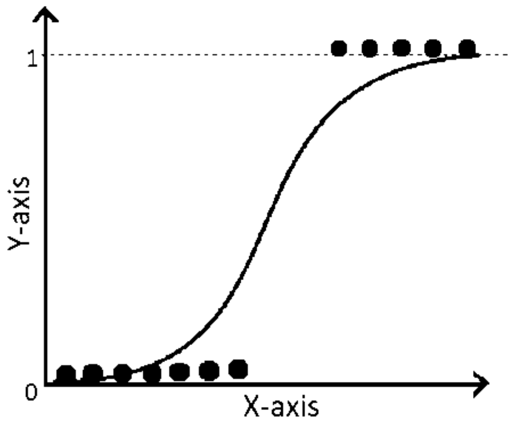

Fig. 3. Logistic Regression [25]

A typical logistic model plot is shown in this figure. The probability never goes below 0 and above 1.

The values are scaled between 0 and 1 when the weighted sum is used in lieu of X. The benefit of using an exponent in the above equation is that the value never goes below zero or above one. Large positive values are scaled toward 1, while large negative numbers are scaled toward 0. The logistic function can be formulated as:

$$f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

The logistic function can be translated as:

$$f(x) = \frac{1}{1+e^{-(B_0 + B_n X_n)}} \quad (2)$$

where e is the natural logarithm base, B_0 and B_n are the model's parameters, and f(x) is the likelihood of a 1. When X is zero, the value of B_0 produces P, and when X is changed to a single unit, Bn modifies the rate at which the probability varies. Since there is a nonlinear relationship between X and Y.

3.3. Confusion Matrix

The confusion matrix summarizes a classifier's effectiveness in categorizing a particular portion of test data. It is a two-dimensional matrix in which an object's actual class index is in one dimension and the classifier assigned in another. The confusion matrix is widely used to represent a specific instance containing two classes, one of which is denoted as the class that is positive, and the other is referred to as the negative class. Table 2 divides the four cells that make up the matrix into four categories: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) [26].

Table 2. Confusion Matrix

	Predicted Positives	***Predicted Negatives***
Actual Positive Instances	# of True Positive instances (TP)	# of False Negative instances (FN)
Actual Negative Instances	# of False Positive instances (FP)	# of True Negative instances (TN)

3.4. Measure and Analysis

The projected groupings provide four distinct results: As anticipated, the actual classification is good. Categorization is advantageous. Since the classifier correctly identifies the positive sample, this result is known as "True Positive," or TP. Not only is the expected classification negative, but the actual classification is also negative. Because the negative sample is accurate, this is a "true negative" (TN) result. The identification was made by the classifier. Whereas the expected classification is positive, the actual classification is negative. This is a "false positive" (FP) result when the positive findings were mistakenly identified as belonging to the negative sample.

Although the anticipated classification is negative, the actual classification is positive. 'False negative' (FN) is what this is. The result arises from the classifier misclassifying the positive sample as negative.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (4)$$

(5)

The accuracy of a model based on binary classification is calculated as the ratio of successfully categorized samples (true outcomes) to total tested samples. The precision is the number of samples accurately identified as positive divided by the total number of samples classified as positive. Recall, often referred to as sensitivity, is calculated by dividing the total number of positive samples by the number of samples that were correctly classified as positive [27].

Table 3. Effectiveness Rating Scale

Percent Range	***Verbal Interpretation***
81%-100%	Highly Effective/ Highly Accurate/ Highly Precise/Highly Sensitive
61%-80%	Effective/ Accurate/ Precise/ Sensitive
41%-60%	Moderately Effective/ Moderately Accurate/ Moderately Precise/ Moderately Sensitive
21%-40%	Slightly Effective/ Slightly Accurate/ Slightly Precise/ Slightly Sensitive
0%-20%	Not Effective/ Not Accurate/ Not Precise/ Not Sensitive

The table 3 will be used to identify the verbal interpretation of accuracy, precision and recall score.

4. Results And Discussion

4.1. Applicants/Faculty Profile

Table 4. Applicants' profile according to Current Position, Position Applied, and Merit Points

Variable	***Recommended***		***Deferred***	
	f	***%***	***f***	***%***
Current Position				
Assistant Professor IV	2	2.1%	0	0.0%
(115-123)	2	2.1%	0	0.0%
Assistant Professor III (106-	1	1.1%	0	0.0%
114)	2	2.1%	0	0.0%
Assistant Professor II (97-	10	10.6	4	4.3%
105)	3	%	0	0.0%
Assistant Professor I (88-	6	3.2%	0	0.0%
96)	30	6.4%	36	37.5
Instructor III (77-87)		31.3		%
Instructor II (66-76)		%		
Instructor I (65-below)	4		1	
Outside Applicant	4		2	1.0%
	3	4.2%	1	2.1%
Position Applied	3	4.2%	3	1.0%
Associate Professor V (152-	4	3.1%	9	3.1%
158)	8	3.1%	2	9.4%
Associate Professor IV	5	4.2%	4	2.1%
(145-151)	4	8.3%	1	4.2%
Associate Professor III	7	5.2%	5	1.0%
(138-144)	7	4.2%	7	5.2%
Associate Professor II (131-	3	7.3%	1	7.3%
137)	4	7.3%	4	1.0%
Associate Professor I (124-		3.1%		4.2%
130)		4.2%		
Assistant Professor IV	17		1	
(115-123)	1		0	1.0%
Assistant Professor III (106-	1	17.7	2	0.0%
114)	5	%	0	2.1%
Assistant Professor II (97-	5	1.0%	1	0.0%
105)	4	1.0%	0	1.0%
Assistant Professor I (88-	9	5.2%	3	0.0%
96)	4	5.2%	4	3.1%
Instructor III (77-87)	5	4.2%	2	4.3%
Instructor II (66-76)	6	9.4%	3	2.1%
Instructor I (65-below)	1	4.3%	5	3.1%
	0	5.2%	3	5.2%
Merit Points	0	6.3%	16	3.1%
Professor (159-above)		1.0%		16.7
Associate Professor V (152-		0.0%		%
158)		0.0%		
Associate Professor IV				
(145-151)				
Associate Professor III				
(138-144)				

Associate Professor II (131-137)				
Associate Professor I (124-130)				
Assistant Professor IV (115-123)				
Assistant Professor III (106-114)				
Assistant Professor II (97-105)				
Assistant Professor I (88-96)				
Instructor III (77-87)				
Instructor II (66-76)				
Instructor I (65-below)				
Total	**56**	**58%**	**40**	**42%**

Table 4 shows the profile of the respondents in terms of their current position, position applied, and merit points earned. These profile variables will later be used as predictors to determine the Faculty Selection Results.

Analyzing the profile of respondents in terms of their current positions based on the provided dataset reveals a diverse range of applicants within an academic institution, highlighting the varying levels of faculty positions as well as the significant portion of outside applicants. The dataset categorizes the respondents by their current positions, ranging from Assistant Professor IV to Instructor I, alongside a category of outside applicants.

Assistant Professors IV, III, II, and I have a relatively low representation among the recommended applicants, with 2 (2.1%) for both Assistant Professor IV and III, 1 (1.1%) for Assistant Professor II, and another 2 (2.1%) for Assistant Professor I. It is also noted that there are no deferred applicants in these categories, suggesting that candidates within these ranks either meet the criteria for recommendation or perhaps are not applying in significant numbers. Meanwhile, Instructors form a larger segment of the internal applicant pool, with Instructor III leading in both recommended (10, 10.6%) and deferred (4, 4.3%) categories, followed by Instructor I and II. Instructor I has 6 (6.4%) recommended applicants, while Instructor II has 3 (3.2%), with none deferred in these latter two ranks. This distribution indicates a more active participation and variation in outcomes among applicants at the instructor level compared to the Assistant Professor ranks.

The position an applicant has applied for can be a strong predictor of the selection outcome due to varying levels of competition and qualification requirements across different academic ranks. For instance, higher academic positions such as Associate Professor V and IV showing 100% recommendation rates suggest that applicants for these positions either meet a very high standard of qualifications or face less competition. In contrast, the relatively higher deferral rates in positions like Assistant Professor I indicate a more competitive field with possibly a larger number of applicants or more stringent selection criteria. Thus, the level of the position applied for can predict the likelihood of being recommended or deferred, with higher positions possibly being less competitive or requiring a unique set of qualifications that fewer applicants possess.

Moving down the merit point scale, there is a visible shift in the distribution of recommendations and deferrals. Associate Professor V and Associate Professor III positions, requiring 152-158 and 138-144 points respectively, maintain favorable recommendation ratios without any or with minimal deferrals. This observation indicates that while high merit points remain a strong indicator of success, the institution exercises a degree of flexibility within certain merit brackets, likely to accommodate the specific requirements or strategic needs of different departments.

However, as the researchers delve into the ranks requiring fewer merit points, the pattern begins to diversify. Assistant Professor IV to Assistant Professor I categories, spanning 115-123 to 88-96 points, exhibit a mixed response with both recommendations and deferrals present, yet with recommendations consistently outpacing deferrals. This suggests that while merit points are critical, other factors may come into play at these levels, possibly including departmental needs, specialization, or other non-point-based achievements.

The scenario changes dramatically for Instructor ranks, especially at the lower end of the merit point spectrum (65 points and below), where no recommendations were made, and deferrals surged to 17%. This stark difference highlights a potential threshold effect, where applicants falling below a certain merit point threshold face significantly reduced chances of recommendation, possibly reflecting a minimum standard of qualifications and competencies expected by the institution.

The data suggests that merit points serve as a strong predictor of the selection outcome. Applicants with higher merit points, particularly those applying for Professor and Associate Professor ranks, have significantly higher recommendation rates compared to those with lower merit points. This pattern indicates that the Faculty Selection Board places considerable weight on the merit points system, which likely reflects an applicant's qualifications, experience, and overall contributions to their field.

Table 5. Applicants' profile according to Demonstration Teaching and Interview Rating

Variable	***Recommended***		***Deferred***	
	f	***%***	***f***	***%***
Teaching				
Demonstration				
	28	29.2%	6	6.3%
Excellent (96-100)	20	20.8%	4	4.2%
Very Satisfactory	8	8.3%	18	18.8%
(88-95)	0	0.0%	6	6.3%
Satisfactory (80-87)	0	0.0%	6	6.3%
Unsatisfactory (70-				
79)				
Poor (69-below)	17	17.7%	1	1.0%
	20	20.8%	5	5.2%
Interview	10	10.4%	13	13.5%
Excellent (96-100)	9	9.4%	20	20.8%
Very Good (88-95)				
Good (80-87)				
Needs Improvement				
(79-below)				
Total	**56**	**58%**	**40**	**42%**

Examining the dataset in terms of teaching demonstration and interview ratings provides valuable insights into the correlation between these evaluation components and the Faculty Selection Board outcomes. The teaching demonstration results reveal a positive trend, with higher ratings directly aligning with increased recommendation rates. Notably, candidates receiving an "Excellent" rating witness a substantial 29.2% recommendation rate, while those with a "Very Satisfactory" rating follow closely with a 20.8% recommendation rate. This suggests a strong association between the quality of teaching demonstrated and the likelihood of a positive outcome, showcasing the board's emphasis on instructional excellence.

Conversely, the interview ratings present a more varied picture. While candidates with an "Excellent" interview rating enjoy an 17.7% recommendation rate, those with a "Very Good" rating have a slightly higher recommendation rate of 20.8%. The noteworthy observation arises in the "Good" category, where the recommendation rate is 10.4%, indicating that a satisfactory interview performance might still lead to a favorable outcome. However, the "Needs Improvement" category displays a considerable challenge, with a 9.4% recommendation rate and a high deferral rate of 20.8%. This suggests that candidates with perceived interview weaknesses face an uphill battle in securing a recommendation.

The direct trend between higher teaching demonstration ratings and increased recommendation rates strongly suggests that this variable is a reliable predictor of success. Candidates who demonstrate excellence in their teaching are more likely to receive favorable outcomes from the Faculty Selection Board. Incorporating teaching demonstration ratings into a predictive model would allow for the identification of candidates with a higher probability of recommendation based on their demonstrated instructional abilities.

Table 6. Logistic Regression Model per Sub-Rank

Variable		***Exp(B)***	***95% CI for Exp(B)***		***B***	***p***
			LL	***UL***		
Instructor I	Intercept	3.44e-236	0.00	Inf	-542.18	1.00
	Total Points	2.729	0.00	Inf	1.00	1.00
	Interview	0.101	0.00	Inf	-2.29	1.00
	Teaching Demonstration	2216.10	0.00	Inf	7.70	1.00
Instructor II	Intercept	9.20e-79	0.00	Inf	-179.68	1.00
	Total Points	6.9909	0.00	Inf	1.94	1.00
	Interview	0.0107	0.00	Inf	-4.54	1.00
	Teaching Demonstration	87.6726	0.00	Inf	4.47	1.00
Instructor III	Intercept	0.000	0.00	Inf	-1287.77	1.00
	Total Points	8948.263	0.00	Inf	9.10	1.00
	Interview	0.147	0.00	Inf	-1.92	1.00
	Teaching Demonstration	1870.583	0.00	Inf	7.53	1.00
Assistant Professor I	Intercept	4.78e-267	0.00	Inf	-613.225	0.999
	Total Points	2.03	0.00	Inf	0.709	1.00
	Interview	1.17	0.00	Inf	0.156	1.00
	Teaching Demonstration	456.38	0.00	Inf	6.123	0.999
Assistant Professor II	Intercept	3.92e+21	0.00	Inf	49.7197	1.00
	Total Points	2.617	0.00	Inf	0.9620	1.00
	Interview	0.984	0.00	Inf	-0.0164	1.00
	Teaching Demonstration	0.209	0.00	Inf	0.9620	1.00
Assistant Professor III	Intercept	9.24e+19	1.13e-77	7.56e+116	45.973	0.686
	Total Points	1.720	0.33830	8.75	0.543	0.513
	Interview	0.815	0.37458	1.77	-0.204	0.606
	Teaching Demonstration	0.369	0.00826	16.50	-0.997	0.607
Assistant Professor IV	Intercept	1.25e-92	0.00	Inf	-211.612	1.000
	Total Points	1.60	0.00	Inf	0.469	1.000
	Interview	1.78	0.00	Inf	0.579	1.000
	Teaching Demonstration	3.68	0.00	Inf	1.302	1.000
Associate Professor I	Intercept	3.35e-121	0.00	Inf	-277.403	1.000
	Total Points	5.45	0.00	Inf	1.696	1.000
	Interview	1.58	0.00	Inf	0.460	1.000
	Teaching Demonstration	1.24	0.00	Inf	0.215	1.000
Associate Professor II	Intercept	1.57e-11	0.00	Inf	-24.87564	1.000
	Total Points	1.002	0.00	Inf	0.00239	1.000
	Interview	1.000	0.00	Inf	-9.09e-5	1.000
	Teaching Demonstration	1.656	0.00	Inf	0.50470	1.000
Associate Professor III	Intercept	1.56e-105	0.00	Inf	-241.325	1.000
	Total Points	2.045	0.00	Inf	0.716	1.000
	Interview	7.47e-5	0.00	Inf	2.013	1.000
	Teaching Demonstration	-3.32e-5	0.00	Inf	-0.560	1.000
Associate Professor IV	Intercept	1.37e-72	0.00	Inf	-165.474	1.000
	Total Points	1.718	0.00	Inf	0.541	1.000
	Interview	0.663	0.00	Inf	-0.411	1.000
	Teaching Demonstration	4.047	0.00	Inf	1.398	1.000
Associate Professor V	Intercept	8.68e-105	0.00	Inf	-30.076	1.000
	Total Points	1.458	0.00	Inf	0.377	1.000
	Interview	1.663	0.00	Inf	0.508	1.000
	Teaching Demonstration	0.541	0.00	Inf	-0.615	1.000

The interview ratings provide valuable insights into an applicant's communication skills, interpersonal qualities, and overall suitability for the academic position. The trend between interview ratings and recommendation rates suggests that, while higher ratings generally align with better outcomes, candidates with satisfactory interviews still stand a chance of being recommended. Conversely, those categorized as needing improvement face challenges in securing recommendations. Integrating interview ratings into predictive models allows for a comprehensive evaluation of an applicant's interpersonal and communication skills, contributing to a more holistic prediction of selection outcomes.

4.2. Logistic Regression Models and Results

In tables 6 and 7, the focused investigation into the association between merit system points, interview rating, demonstration teaching rating, and the likelihood of receiving a recommendation for a Plantilla Position among applicants, we still employed a binary logistic regression model. Again, this model aimed to predict the binary outcome of recommendation (coded as 1) or deferral (coded as 0) based on the specified independent variables.

In the instructor level applications, our statistical analysis for Instructor 1 yielded a significant chi-square statistic ($\chi^2(3)$ = 11.1, p = 0.011), Instructor 2 ($\chi^2(3)$ = 4.50, p = 0.212), Instructor 3 ($\chi^2(3)$ = 19.4, p = <0.001), rejecting the null hypothesis for Instructor 1 and 3 emphasizing the critical predictive role of merit points, interview rating, and demonstration teaching rating in determining the Faculty Selection Result in these levels. The model's pseudo-R^2 values, ranging from 0.750 to 1.00 for Instructor 1 and 0.750 to 1.00 for Instructor 3, indicate that these variables collectively account for approximately 75.0% to 100% of the variance in Plantilla Position Application outcomes for Instructor 1 and approximately 75% to 100% of the variance in Plantilla Position Application outcomes for Instructor 3, underscoring their substantial influence on the Faculty Selection Results.

Table 7. Logistic Regression Results for the prediction of faculty selection board results from the total points, interview rating, and demonstration teaching rating earned by the candidate based on their current position and position applied for

	Deviance	*AIC*	R^2_{McF}	R^2_{CS}	R^2_N	χ^2	*df*	*p*	*Accuracy*	*Specificity*	*Sensitivity*	*Predicted*	
												Deferred	*Recommended*
Instructor I	2.13e-10	8.00	1.000	0.750	1.000	11.1	3	0.011	1.00	1.00	1.00	100%	100%
Instructor II	4.66e-10	8.00	1.000	0.675	1.000	4.50	3	0.212	1.00	1.00	1.00	100%	100%
Instructor III	3.56e-9	8.00	1.000	0.750	1.000	19.4	3	<0.001	1.00	1.00	1.00	100%	100%
Assistant Professor I	8.07e-10	8.00	1.000	0.743	1.000	16.3	3	<0.001	1.00	1.00	1.00	100%	100%
Assistant Professor II	2.19e-10	8.00	1.000	0.632	1.000	5.00	3	0.172	1.00	1.00	1.00	100%	100%
Assistant Professor III	3.75	11.7	0.697	0.616	0.825	8.62	3	0.035	0.778	0.750	0.800	75%	80%
Assistant Professor IV	2.43e-10	8.00	1.000	0.632	1.000	10.0	3	0.018	1.00	1.00	1.00	100%	100%
Associate Professor I	4.36e-10	8.00	1.000	0.709	1.000	16.0	3	0.001	1.00	1.00	1.00	100%	100%
Associate Professor II	2.61e-10	8.00	1.000	0.750	1.000	8.32	3	0.040	1.00	1.00	1.00	100%	100%
Associate Professor III	4.66e-10	8.00	1.000	0.675	1.000	4.50	3	0.212	1.00	1.00	1.00	100%	100%
Associate Professor IV	2.76e-10	8.00	1.000	0.720	1.000	7.64	3	0.054	1.00	1.00	1.00	100%	100%
Associate Professor V	2.46e-10	8.00	1.000	0.632	1.000	5.00	3	0.172	1.00	1.00	1.00	100%	100%

However, delving into the logistic regression coefficients in Instructor 1, a model coefficient for total merit points (β = 1.00, p = 1.00), for demonstration teaching rating (β = 7.70, p = 1.00), and for interview rating (β = -2.29, p = 1.00) reveals a not statistically significant relationship between merit points, demonstration teaching rating, interview rating and Faculty Selection Results. The result is the same for Instructor 3 with a model coefficient for total merit points (β = 9.10, p = 1.00), for demonstration teaching rating (β = 7.53, p = 1.00), for interview rating (β = -1.92, p = 1.00) . Nevertheless, the model achieved a high accuracy rate, correctly classifying 100% of cases for Instructor 1, and 100% for Instructor 2 and 3, with sensitivity and specificity rating of both 100%. Recommended results were correctly predicted in 100% of cases same with deferred results for Instructor 1, 100 % in both recommended and deferred results for Instructor 2, and 100% in both recommended and deferred results for Instructor 3.

In the assistant professor level applications, our statistical analysis for Assistant Professor 1 yielded a significant chi-square statistic ($\chi^2(3) = 16.3, p < 0.001$), Assistant Professor 2 ($\chi^2(3) = 5.00, p = 0.172$), Assistant Professor 3 ($\chi^2(3) = 8.62, p = 0.035$), and Assistant Professor 4 ($\chi^2(3) = 10.0, p = 0.018$), all rejecting the null hypothesis for all assistant professor levels emphasizing the critical predictive role of merit points, interview rating, and demonstration teaching rating in determining the Faculty Selection Result in these levels. The model's pseudo-R^2 values, ranging from 0.754 to 1.00 for Assistant Professor 1, from 0.632 to 1.00 for Assistant Professor 2, from 0.616 to 0.825 for Assistant Professor 3, and 0.632 to 1.00 for Assistant Professor 4, indicate that these variables collectively account for approximately 75.4% to 100% of the variance in Plantilla Position Application outcomes for Assistant Professor 1, approximately 63.2% to 100% of the variance in Plantilla Position Application outcomes for Assistant Professor 2, approximately 61.6% to 82.5% of the variance in Plantilla Position Application outcomes for Assistant Professor 3, and approximately 75.4% to 100% of the variance in Plantilla Position Application outcomes for Assistant Professor 4, underscoring their substantial influence on the Faculty Selection Results.

However, delving into the logistic regression coefficients in Assistant Professor 1, a model coefficient for total merit points (β = 0.709, p = 1.00), for demonstration teaching rating (β = 6.123, p = 0.99), and for interview rating (β = 0.156, p = 1.00) reveals not statistically significant relationship between merit points, demonstration teaching rating, interview rating and Faculty Selection Results. The result is the same for Assistant Professor 2, Assistant Professor 3, and Assistant Professor 4. Nevertheless, the model achieved a high accuracy rate, correctly classifying 100% of cases for Assistant Professor 1, also 100% for Assistant Professor 2, 77.8% for Assistant Professor 3, and 100% for Assistant Professor 4 with sensitivity if not equal are higher than specificity rating. Recommended results were correctly predicted in 100% of cases same with deferred results for Assistant Professor 1, 100 % in both recommended and deferred results for Assistant Professor 2, 80% recommended results and 75% deferred results were predicted for Assistant Professor 3, and 100% in both recommended and deferred results for Assistant Professor 4.

Lastly, in the associate professor level applications, our statistical analysis for Associate Professor 1 yielded a significant chi-square statistic ($\chi^2(3) = 16.0, p = 0.001$), Associate Professor 2 ($\chi^2(3) = 8.32, p = 0.040$), Associate 3 ($\chi^2(3) = 4.50, p = 0.212$), Associate 4 ($\chi^2(3) = 7.64, p = 0.054$), and Associate 5 ($\chi^2(3) = 5.00, p = 0.172$), rejecting the null hypothesis for associate professor 1 and 2 levels emphasizing the critical predictive role of merit points, interview rating, and demonstration teaching rating in determining the Faculty Selection Result in these levels. The model's pseudo-R^2 values, ranging from 0.79 to 1.00 for Associate Professor 1, and 0.750 to 1.00 for Associate Professor 2, indicate that these variables collectively account for approximately 79% to 100% of the variance in Plantilla Position Application outcomes for Associate Professor 1, and approximately 75% to 100% of the variance in Plantilla Position Application outcomes for Associate Professor 2, underscoring their substantial influence on the Faculty Selection Results.

However, delving into the logistic regression coefficients in Associate Professor 1, a model coefficient for total merit points ($\beta = 1.696$, $p = 1.00$), for demonstration teaching rating ($\beta = 0.215$, $p = 1.00$), and for interview rating ($\beta = 0.460$, $p = 1.00$) reveals not statistically significant relationship between merit points, demonstration teaching rating, interview rating and Faculty Selection Results. The result is the same for Associate Professor 2 and Associate Professor 3. Nevertheless, the model achieved a high accuracy rate, correctly classifying 100% of cases for all Associate Professor Levels with sensitivity and specificity with also100% rating. Recommended results were correctly predicted in 100% of cases same with deferred results for all Associate Professor Levels.

4.3. Results of Testing Data Using the Logistic Regression Models

The True Positives (TP) are displayed in Table 8; 50 cases were accurately predicted as positive by the model. False Positives (FP): Thirteen truly negative occurrences were mistakenly projected by the model as positive. True Negatives (TN): Twenty-seven cases were appropriately predicted by the model as negative. False Negatives (FN): Six occurrences that were actually positive were mistakenly projected by the model as negative. We can calculate other metrics, such as accuracy, precision, and recall, to assess the performance of the model based on these numbers.

Table 8. Confusion Matrix generated by Logistic Regression Models

	Predicted Positives	***Predicted Negatives***	***Overall Classification***
Actual Positive Instances	50	13	63
Actual Negative Instances	6	27	33
Truth Overall	**56**	**40**	**96**

With respect to the overall categorization, it can be stated that there are 63 (50 TP + 13 FN) occurrences that are truly positive overall. Overall Classification of Actual Negative cases: There are 33 cases overall that are truly negative (6 FP + 27 TN).

Table 9. Performance Metrics

Rank	***Percentage***	***Verbal Interpretation***
Accuracy	80%	Accurate
Precision	79%	Precise
Recall	89%	Highly Sensitive

Table 9 shows the result of the performance metrics. Accuracy: Accuracy is the percentage of cases properly categorized out of all instances. With an accuracy of 80%, the model was able to classify 80% of the positive and negative instances in the dataset with accuracy. It shows the overall accuracy of the model's predictions.

Out of all cases anticipated as positive, precision quantifies the percentage of accurately predicted positive instances. With a precision of 79%, 79% of the occurrences that the model predicted as positive were in fact positive. Precision evaluates the model's capacity to prevent false positives by concentrating on the accuracy of positive predictions.

Recall, which is a statistical measure of the proportion of accurately predicted positive cases among all actual positive instances, is also referred to as Sensitivity or True Positive Rate. With an 89% recall rate, the model successfully recognized 89% of all real positive occurrences. The capacity of the model to detect all positive cases and steer clear of false negatives is the main emphasis of recall.

Regarding the logistic regression models used in public institutions of higher learning in the Philippines for faculty selection and promotion, an accuracy of 80% means that, in 80% of the cases, the model's predictions come true. A 79% accuracy indicates that 79% of the cases correspond to the positive predictions made by the model (professor chosen or promoted). A recall of 89% indicates that the model effectively identifies 89% of all actual positive instances (faculty who should be selected or promoted). When taken as a whole, these indicators give stakeholders insight into the effectiveness of the models used for logistic regression and show them how well the algorithms are selecting faculty members for promotion and selection.

5. Conclusion

Based on the findings and discussions outlined, the following conclusions were made.

(1) Effectiveness of Logistic Regression Models: Based on the performance metrics provided (accuracy, precision, recall), it can be concluded that the logistic regression models developed for faculty selection and promotion in public higher education institutions in the Philippines exhibit 80% reasonable accuracy and effectiveness. The models demonstrate the ability to correctly classify faculty members and effectively identify candidates for selection or promotion.

(2) Significance of Predictive Analytics in Education: The utilization of predictive analytics, particularly logistic regression models, showcases the potential of data-driven decision-making in the education sector. By leveraging machine learning techniques, institutions can enhance their faculty selection and promotion processes, leading to more efficient resource allocation and improved academic outcomes.

(3) Implications for Institutional Policy and Practice: The study's conclusions emphasize how crucial it is to include predictive modeling in institutionalized procedures and regulations that deal with hiring, promoting, and evaluating educators. Institutions can use the insights gained from the logistic regression models to inform strategic decisions, allocate resources effectively, and support the professional development of faculty members, ultimately enhancing the overall quality and competitiveness of the education system.

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