Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 21, 2026

PREDICTIVE MODELING AND EXPLAINABILITY OF STUDENT EMPLOYABILITY IN THE PHILIPPINES USING RANDOM FOREST AND SHAPLEY ADDITIVE EXPLANATIONS

Cris Norman P. Olipas* Nueva Ecija University of Science and Technology, Cabanatuan, Philippines olipas.cris@gmail.com

* Corresponding author

ABSTRACT

Aim/Purpose	This study aims to analyze and predict the employability outcomes of higher education students in the Philippines using data-driven predictive modeling. It aims to identify the student attributes that most strongly influence employability, thereby supporting evidence-based curriculum development and workforce alignment initiatives.
Background	Graduate employability remains a challenge in the Philippines due to persistent gaps between higher education outcomes and labor market expectations. While prior studies emphasize technical competencies, there is limited evidence on the role of non-academic student attributes in predicting employability, particularly through interpretable predictive approaches. This study addresses this gap by examining employability-related traits using machine learning techniques.
Methodology	A publicly available dataset of 2,982 anonymized student records from mock interviews conducted across Philippine higher education institutions was analyzed. Employability was treated as a binary outcome variable. Predictive models were developed with Random Forest selected as the primary model based on overall performance. Model interpretation was conducted using Shapley Additive Explanations (SHAP) analysis to identify the most influential student attributes.
Contribution	The study demonstrates how interpretable machine learning can be used to evaluate graduate employability and identify key attributes shaping workforce readiness. The findings offer practical value for higher education institutions

Accepting Editor Geoffrey Z. Liu │ Received: October 9, 2025 │ Revised: January 1, January 5, 2026 │ Accepted: January 5, 2026.

Cite as: Olipas, C. N. P., (2026). Predictive modeling and explainability of student employability in the Philippines using Random Forest and Shapley Additive Explanations. *Interdisciplinary Journal of Information, Knowledge, and Management, 21,* Article 2. https://doi.org/10.28945/5690

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	and policymakers seeking data-driven approaches to curriculum design and student development.
Findings	The Random Forest model showed strong predictive performance in classifying employability outcomes. SHAP analysis revealed that mental alertness, general appearance, and the ability to present ideas were the most influential factors affecting employability, indicating the importance of cognitive and professional presentation skills.
Recommendations for Practitioners	Higher education institutions should strengthen instructional strategies and student development programs that enhance cognitive readiness, professional presentation, and communication-related competencies. Career services and industry partners are encouraged to collaborate in aligning training initiatives with employability needs.
Recommendations for Researchers	Future studies should explore additional predictive models and incorporate broader datasets to further validate the determinants of employability. Including demographic and academic variables may deepen understanding of employability dynamics.
Impact on Society	By identifying critical employability attributes, this study supports more responsive and inclusive higher education practices. Data-driven employability strategies can contribute to improved workforce readiness and reduced graduate unemployment in the Philippines.
Future Research	Future research may examine longitudinal employability outcomes and assess the application of predictive analytics in institutional decision-making contexts. Attention to ethical considerations, including transparency and fairness, is also recommended.
Keywords	machine learning, predictive modeling, random forest, SHAP, student employability

INTRODUCTION

In the Philippines, ensuring that higher education graduates are employable remains a significant challenge, reflecting broader global concerns about aligning academic outcomes with labor market needs. Employment statistics highlight the urgency of this issue, as the national employment rate stood at 3.8% in September 2025, according to the Philippine Statistics Authority (Clores, 2025). While this figure represents a slight improvement, it continues to signal persistent issues in workforce readiness, particularly among new graduates entering the labor market. Employability is widely recognized as a multidimensional concept shaped by personal traits, contextual elements, and labor market conditions (Behle, 2020). Addressing employability requires collaboration among higher education institutions, students, employers, and government agencies; however, persistent gaps still exist between academic training and industry requirements (Cheng et al., 2021; Matherly & Tillman, 2015).

Scholars highlight that employability development must go beyond technical knowledge to include transferable skills, adaptability, and lifelong learning abilities fostered through experiential and authentic learning experiences (Choi-Lundberg et al., 2024; Oliver, 2015; Yorke, 2006). However, evidence reveals ongoing misalignments between curriculum outputs and employer expectations, leading to skill gaps and diminished workforce readiness (Eldeen et al., 2018; Reddy, 2019; Small et al., 2017). This emphasizes the need for integrated approaches that bridge education and employment systems, embedding both cognitive and professional skills within higher education (Bhola & Dhanawade, 2013; Knight & Yorke, 2003).

In response to these challenges, data-driven predictive analytics have increasingly been applied to examine employability outcomes. Predictive models, such as Random Forest, Logistic Regression, Support Vector Machine, and K-Nearest Neighbors, can evaluate measurable student characteristics and generate insights into the key factors influencing employability (A. D. P. Kumar et al., 2025). When combined with interpretability techniques, these approaches allow researchers and institutions to move beyond prediction accuracy and toward a clearer understanding of why certain attributes matter. However, existing studies often focus either on predictive performance or on general employability determinants, with limited attention to interpretable, context-specific evidence in developing country settings such as the Philippines. This gap highlights the need for students who integrate predictive accuracy with transparent explanation to support actionable decision-making in higher education.

Accordingly, this study aims to identify and evaluate the key student attributes that most significantly influence employability potential in the Philippine higher education context using predictive modeling. Rather than emphasizing algorithmic comparison alone, the study prioritizes the interpretation of influential traits to generate practical insights that can guide curriculum enhancement, student development initiatives, and institutional planning.

At the same time, advancing graduate employability must be viewed through the lens of inclusive and sustainable education. Ensuring equitable opportunities for all students aligns with national development priorities and the United Nations Sustainable Development Goals, particularly SDG 4 (Quality Education) and SDG 5 (Gender Equality). Prior research indicates that employment outcomes often differ across gender and social groups due to wage gaps, occupational segregation, and unequal access to opportunities (Martin et al., 2020). Although the dataset used in this study does not contain gender-disaggregated variables, this limitation highlights the importance of embedding inclusivity and equity markers, such as gender, socioeconomic status, and geographic location, into future employability analytics. Doing so ensures that predictive models not only enhance institutional planning but also contribute to building a fair, adaptive, and sustainable higher education system that prepares all graduates for meaningful participation in the labor market.

By combining predictive analytics with model interpretability, this study provides empirical, context-specific evidence on determinants of employability in the Philippines. Its findings are intended to support higher education institutions, policymakers, and stakeholders in designing more responsive, inclusive, and data-informed strategies that enhance graduate readiness and strengthen alignment between education and labor market demands.

Research Objectives

This study aims to achieve the following objectives:

1. To evaluate the predictive capability of selected machine learning approaches in identifying student employability outcomes in the Philippines based on measurable student attributes.
2. To identify and analyze the key student traits that most significantly influence employability outcomes through feature selection importance analysis using Shapley Additive Explanations (SHAP) values derived from the best-performing model.
3. To interpret and explain the predictive insights generated by the model through SHAP analysis and provide evidence-based recommendations that can guide higher education institutions, curriculum designers, and policymakers in enhancing graduate employability.

Literature Review

Key Student Attributes and Factors Influencing Employability

Understanding employability requires identifying the personal traits, skills, and experiences that contribute to a graduate's success in the workforce. Research consistently shows that employability is shaped by a combination of cognitive abilities, personality, education, social skills, and professional behaviors. Early studies, such as those by Juhdi et al. (2010), emphasized the role of formal career management practices, training, job experiences, education, and tenure, noting that these factors significantly influence both internal and external employability. Informal career management practices, in particular, were found to relate strongly to external employability, highlighting the importance of proactive student engagement in career development.

Cognitive and interpersonal skills, including academic performance, problem-solving, communication, collaboration, and personality traits, are widely recognized as critical for employability (Finch et al., 2013; Hogan et al., 2013). Abbas and Sagsan (2019) further highlighted that skills, knowledge, and professional attitudes are key employability attributes, revealing a substantial gap between student performance and industry expectations. Developing these skills ensures that graduates can meet the demands of the workplace and adapt to changing professional environments.

Experiential learning, such as internships, work-integrated learning, and formal or informal career management practices, provides practical exposure and strengthens employability outcomes (Choi-Lundberg et al., 2024; Juhdi et al., 2010). Clarke (2017) proposed a framework that integrates human capital, social capital, individual attributes, behaviors, perceived employability, and labor market factors, highlighting that traditional skill-focused approaches may overlook critical experiential dimensions. These findings emphasize that employability is not static but evolves through active engagement in professional and educational experiences.

In the Philippines, employability is increasingly understood as a combination of cognitive, interpersonal, and experiential factors that align education with labor market demands. Cognitive skills, such as critical thinking and problem-solving, are foundational but often moderately developed among graduates due to the traditional emphasis on rote learning (Alvero, 2025; Corpin, 2025). Socioemotional or interpersonal skills, including communication, teamwork, and adaptability, are essential for workplace success; yet, gaps remain, as curricula primarily focus on academic achievements (Acosta et al., 2017). Experiential factors, such as internships, industry collaborations, and applied learning opportunities, are crucial in bridging the gap between education and employment, as graduates lacking real-world experience may struggle to secure jobs matching their qualifications (Corpin, 2025). While cognitive and socioemotional skills are critical, technical skills and vocational training also play a crucial role in certain sectors of the Philippine workforce.

More recent evidence reinforces and extends these findings. Siddhanth et al. (2025) identified critical attributes that influence engineering students' employability, including academic performance, internships, student demographics, and prior academic background. Their study applied machine learning models and found that a Voting Classifier combining Random Forest and XGBoost could predict employability with high accuracy, illustrating the predictive value of these attributes. Taeza-Cruz et al. (2024) similarly identified internship marks, credit hours, department, and specialization as critical predictors for engineering students, using decision tree-based models (J48) that are both interpretable and accurate. Bhattacherjee and Kukreja (2025) applied Support Vector Machines to computer science students. They found high predictive performance across accuracy, recall, F1-score, and MCC, highlighting the potential of data-driven approaches in targeting student skill gaps.

Together, these findings underscore that employability is a dynamic capability shaped by technical skills, interpersonal competencies, experiential learning, and proactive career engagement. By identifying and prioritizing key student attributes, educators and policymakers can design effective career readiness programs and interventions that align graduates' capabilities with labor market demands.

CURRENT CHALLENGES IN ASSESSING EMPLOYABILITY

Accurately assessing employability remains a major challenge due to its complex nature, reliance on diverse data, and the difficulty of isolating the impact of education and training from other factors

(Perez et al., 2010; Williams et al., 2015). Traditional measures, such as employment outcomes or institutional rankings, often provide an incomplete picture, emphasizing outcomes rather than the individual capabilities that contribute to employability (Harvey, 2001). Moreover, subjective indicators of employability, while common, may lack consistency and fail to capture the full range of skills, attributes, and contextual influences that shape graduate success (Neroorkar, 2022).

To address these limitations, several studies advocate for more objective and systematic approaches. Agrawal (2019) demonstrated that composite scores based on measurable student attributes can identify employable candidates with significantly greater precision than single metrics or subjective judgments. Similarly, Williams et al. (2015) proposed a conceptual framework that integrates career management, capital, and contextual dimensions, providing a structured basis for assessing employability within educational settings. Andrews and Russell (2012) also emphasized the importance of critical evaluation, highlighting the need to align institutional strategies with actual outcomes and employer requirements.

Recent advances in data-driven methods and machine learning provide further opportunities to enhance employability assessment. Mezhoudi et al. (2021) reviewed current approaches that use predictive modeling to forecast student employability, emphasizing the importance of identifying relevant factors and aligning predictions with labor market needs. These approaches enable the simultaneous analysis of multiple measurable attributes and provide interpretable insights when combined with techniques such as SHAP values. By adopting holistic, objective, and data-informed assessment methods, stakeholders, including educators, career services, and policymakers, can better understand employability determinants and implement targeted interventions to improve graduate outcomes.

MACHINE LEARNING FOR EMPLOYABILITY PREDICTION

Predictive modeling has emerged as a valuable approach in educational data mining and learning analytics, providing insights into student success and outcomes (Brooks & Thompson, 2017). By analyzing patterns in student behavior, performance, and engagement, predictive models can forecast academic achievement, course completion, and overall employability (Liz-Domínguez et al., 2019; Smith et al., 2012). These models enable educators and institutions to implement targeted interventions, thereby enhancing student support and improving retention rates. Beyond education, predictive modeling has also proven effective in other fields, such as healthcare, demonstrating the versatility of these techniques in identifying high-risk cases and guiding resource allocation (Hodgman, 2008).

Machine learning techniques, including Logistic Regression, Support Vector Machines (SVM), K-Nearest Neighbors, and Random Forest, have been widely applied to predict student employability and performance (Almalawi et al., 2024; Casuat & Festijo, 2019; Rivera et al., 2023). Among these, Random Forest consistently demonstrates superior performance. Its ensemble-based approach allows it to handle large numbers of predictor variables, capture complex nonlinear relationships, and provide measures of variable importance (Strobl et al., 2009; Touw et al., 2012). Random Forest has been successfully applied to predict student employability, academic outcomes, persistence, and even dropout behavior, often outperforming other machine learning algorithms in accuracy and reliability (Baffa et al., 2023; HemaMalini et al., 2020; D. Kumar et al., 2024; Saini et al., 2021; Vinutha & Yogisha, 2021).

Despite the demonstrated utility of these models, previous studies have several limitations that justify further investigation. Many earlier studies rely on relatively small or localized datasets, which may not capture the diversity of student populations or evolving labor market requirements. Additionally, most studies focus on a limited set of attributes, primarily academic performance, while overlooking experiential factors such as contextual variables (Bhattacherjee & Kukreja, 2025; Siddhanth et al., 2025; Taeza-Cruz et al., 2024). There is also a lack of interpretability in some studies, making it difficult for educators and policymakers to understand which factors most strongly influence employability outcomes. These gaps highlight the need for recent, comprehensive studies that integrate multiple student attributes, employ advanced ML algorithms, and provide interpretable results for actionable decision-making.

The effectiveness of Random Forest lies not only in its high predictive accuracy but also in its interpretability. Techniques such as feature importance rankings and SHAP values allow researchers and educators to identify which student traits and performance indicators most influence predicted outcomes (Remegio, 2024; Tang et al., 2024). This capability aligns with the objectives of the present study, which seeks to assess the accuracy of Random Forest in predicting employability among Filipino students and to determine the student attributes that contribute most significantly to employability outcomes. By leveraging Random Forest and interpretive techniques like SHAP, institutions can gain actionable insights for curriculum design, career guidance, and policy development.

Table 1 summarizes recent studies that applied machine learning to predict student employability, highlighting the key attributes considered, data sources, student majors, and the algorithms used. This overview illustrates the current development in the field and provides a rationale for the selection of the four ML techniques in the present study.

Table 1. Summary of recent machine learning studies predicting student employability

Study	Key attributes/factors	Data source (region country)	Student major discipline	ML technique used
Siddhanth et al. (2025)	CGPA, internships, demographics (age, gender, hostel/ residency), academic backlogs	India	Engineering students	Voting Classifier (Random Forest + XGBoost), Logistic Regression, SVM, K-NN
Taeza-Cruz et al. (2024)	Internship marks, credit hours, department, specialization	Oman	Engineering students	J48, RepTree, Random Forest
Bhattacherjee and Kukreja (2025)	Soft skills, problem-solving skills, technical skills, innovation skills, personal qualities, perception towards employability	India	Computer science students	SVM, Decision Tree, ANN

This table demonstrates the diversity of attributes and ML approaches in recent studies and confirms that the algorithms chosen in this study are supported by contemporary research. It also highlights the importance of considering multiple student factors in developing interpretable and accurate employability prediction models.

METHODOLOGY

This study used an experimental, quantitative design with retrospective student data. Its main goal was to develop, test, and compare several machine learning models, including Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression, to predict student employability in the Philippines. The models' performance was assessed using standard measures, including accuracy, precision, recall, and F1-score. Statistical tests were also conducted to compare the models to see how well they perform in predicting the outcomes. To make the results more understandable, Shapley Additive Explanations (SHAP) were applied to the best-performing model, highlighting which student traits most strongly influenced employability. Figure 1 illustrates the predictive modeling pipeline for student employability.

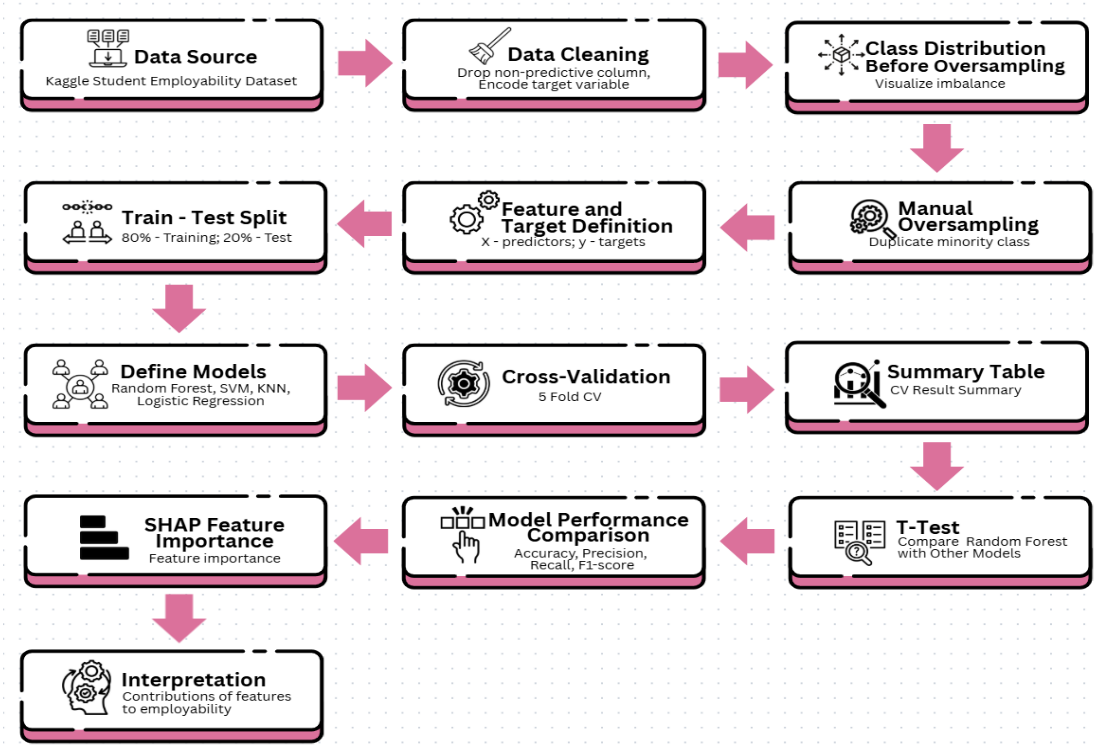

Figure 1. Predictive modeling pipeline for student employability

The dataset used in this study was obtained from a publicly available Kaggle data source, comprising N = 2,982 student records from mock interviews conducted by various universities across the Philippines (https://www.kaggle.com/code/ryanangelodelacruz/student-employability-eda-mla). Records were included if they contained complete information on the following student traits: mental alertness, general appearance, physical condition, manner of speaking, self-confidence, ability to present ideas, communication skills, and student performance rating in OJT. Records with missing attributes were excluded. Demographic information, such as age, gender, and program of study, was not utilized as it was not part of the dataset. The target variable, employability, was binary-coded as "Employable" and "Less Employable". Table 2 shows the predictor variables used in the study, their data types, and descriptions, providing a clear overview of the attributes considered for employability prediction.

Table 2. Predictor variables for student employability modeling

Predictor variable	Data types	Description
General Appearance	Ordinal	Evaluates the student's overall physical presentation and grooming during the interview
Manner of Speaking	Ordinal	Assesses clarity, tone, and confidence in verbal expression
Physical Condition	Ordinal	Measures general health, posture, and energy level
Mental Alertness	Ordinal	Evaluates attentiveness, focus, and responsiveness during interaction

Predictor variable	Data types	Description
Self-Confidence	Ordinal	Assesses the student's confidence in expressing ideas and handling questions
Ability to Present Ideas	Ordinal	Measures effectiveness in structuring and presenting thoughts clearly
Communication Skills	Ordinal	Evaluates clarity, fluency, and appropriateness of communication
Student Performance Rating	Ordinal	Supervisor's rating of student performance
Class (Target Variable)	Nominal	Binary employability classification (less employable, employable)

The dataset was pre-processed to ensure suitability for model training. Records with missing values in any of the relevant features were excluded to maintain data integrity. Categorical features were properly encoded using ordinal encoding, and outliers were examined through descriptive statistics and retained when they represented valid variations in student traits. Analysis of the class distribution revealed a significant majority of "Employable" cases; to mitigate this imbalance, manual over-sampling was applied by duplicating minority class samples ("Less Employable"), ensuring that the model could learn patterns from both classes effectively. No additional scaling was applied at this stage.

Predictor variables (X) included all student traits, while the target variable (Y) represented employability status. The dataset was then split into 80% training and 20% testing subsets. No further resampling was performed after the split to preserve data integrity.

The four machine learning algorithms were defined and trained. Each model underwent 5-fold cross-validation using GridSearchCV to optimize hyperparameters, and a summary table was generated to consolidate the cross-validation results for all models. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC as evaluation metrics. Statistical tests were conducted to compare predictive capabilities among the algorithms.

For interpretability, Shapley Additive Explanations (SHAP) were applied to the best-performing model after evaluation. SHAP summary and dot plots were used to visualize each feature's contribution and the direction of its impact on employability predictions, allowing identification of the most influential student traits

All analyses were performed using Python 3.10, with scikit-learn for modeling and hyperparameter tuning, and SHAP for model explainability. The dataset, publicly available on Kaggle, is anonymized and contains no identifiable student information, ensuring compliance with ethical standards and data privacy regulations. Random seeds were fixed to ensure reproducibility of train-test splits and model results.

RESULTS

COMPARATIVE PERFORMANCE EVALUATION OF MACHINE LEARNING ALGORITHMS IN PREDICTING STUDENT EMPLOYABILITY

To establish the comparative predictive capabilities of the selected machine learning models, their performance was first evaluated through cross-validation. Table 3 shows the cross-validation performance of machine learning models.

Table 3. Cross-validation performance of machine learning models

Statistics	Random forest	Logistic regression	SVM	KNN
Mean Accuracy	0.9042	0.5969	0.8623	0.8905
Standard Deviation	0.0140	0.0190	0.0131	0.0164

To determine whether the observed performance differences among models were statistically meaningful, a series of t-tests was conducted comparing Random Forest with the other algorithms. Table 4 presents the statistical significance using a t-test between Random Forest and other models.

Table 4. Statistical significance (t-test) between Random Forest and other models

Comparison	T-statistic	p-value	Interpretation
Random Forest vs. Logistic Regression	29.1615	0.0000	Significant Difference. Random Forest performs better
Random Forest vs. SVM	4.8927	0.0012	Significant Difference. Random Forest performs better
Random Forest vs. KNN	1.4267	0.1915	Not Significant. Comparable Performance

Beyond cross-validation, the models were further evaluated using an independent test set to verify their real-world generalization and reliability across key performance metrics. Table 5 shows the test set performance metrics of the four machine learning models.

Table 5. Test set performance metrics

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.9220	0.9220	0.9220	0.9220
KNN	0.8829	0.8829	0.8829	0.8829
SVM	0.8555	0.8619	0.8555	0.8549
Logistic Regression	0.5376	0.5389	0.5376	0.5336

The results, as shown from the tables above, reveal that the Random Forest Algorithm achieved the highest predictive accuracy with a mean value of 0.9042 among the evaluated models, followed by KNN with a mean value of 0.8905, SVM with a mean value of 0.8623, and Logistic Regression with a mean value of 0.5969. The relatively low standard deviation values across all models indicate stable and consistent performance during cross-validation. Statistical analysis, as shown in Table 4, further confirmed that the performance of Random Forest was significantly better than both Logistic Regression and SVM ($p < 0.05$), suggesting that ensemble learning methods are more effective in capturing complex relationships between student attributes and employability outcomes. However, its difference from KNN was not statistically significant, implying these two models demonstrate comparable predictive capabilities. When evaluated on the test dataset, as shown in Table 5, Random Forest consistently recorded the highest scores in all metrics, including accuracy, precision, recall, and F1-score, indicating its strong balance between sensitivity and reliability in prediction.

These findings imply that Random Forest is the most suitable model for predicting student employability in the Philippine context, given its strong and consistent performance across all evaluation metrics. The results highlight the model's ability to handle diverse and possibly nonlinear interactions among student-related variables. The comparable results between Random Forest and KNN also suggest that simpler, instance-based methods may still serve as viable alternatives when computational efficiency or interpretability is prioritized. For higher education institutions, these results emphasize the potential of advanced machine learning techniques to support data-driven decision-making, enabling educators, administrators, and policymakers to identify employability determinants more accurately and design targeted programs that enhance graduate readiness for the labor market.

Identification of Key Predictive Factors Influencing Student Employability through SHAP Feature Importance Analysis

Figure 2 presents the SHAP feature importance by class for student employability, with the top five features highlighted.

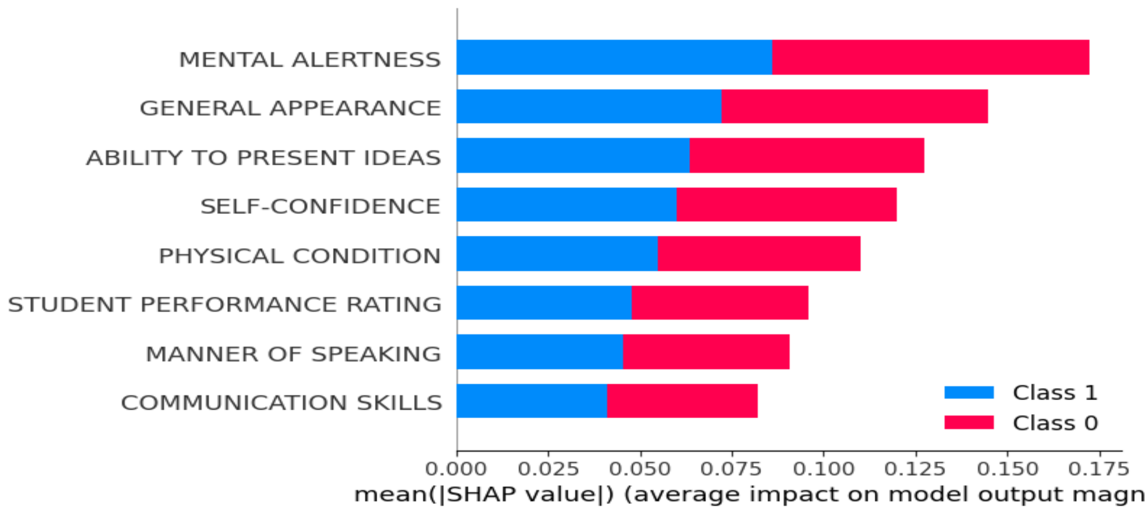

Figure 2. SHAP feature importance by class for student employability

The SHAP feature importance analysis highlights that the most significant traits influencing employability outcomes are mental alertness, general appearance, and the ability to present ideas. Among these, mental alertness stands out as the dominant predictor, with high alertness substantially increasing the likelihood of being classified as employable, while low alertness strongly contributes to predictions of less employability. This finding highlights the importance of cognitive readiness and attentiveness as key competencies highly valued by employers.

General appearance emerges as the second most influential trait, reflecting the role of professional demeanor and appearance in shaping perceptions of employability. Meanwhile, the ability to present ideas also ranks prominently, indicating that effective communication and clarity of thought are decisive factors in employability outcomes. Following these traits, self-confidence and physical condition also play significant roles, albeit to a lesser extent, highlighting the importance of confidence and overall well-being in employment readiness.

Interestingly, while student performance ratings during on-the-job training (OJT) and manner of speaking contribute to the predictions, their relative impact is lower compared to the top-ranking soft skills and behavioral attributes. Communication skills rank as the least influential, suggesting that while relevant, they function more as supportive rather than primary determinants of employability within the model.

The Random Forest model, interpreted through SHAP values, reveals that employability is most significantly influenced by cognitive sharpness, professional appearance, and the ability to articulate ideas, with academic performance and technical indicators playing a secondary role. This highlights the importance of soft skills and personality traits over purely academic achievements in determining employability outcomes.

INTERPRETATION OF SHAP-DERIVED INSIGHTS AND IMPLICATIONS FOR HIGHER EDUCATION

Figure 3 illustrates the SHAP Dot summary, showing the feature's influence on student employability.

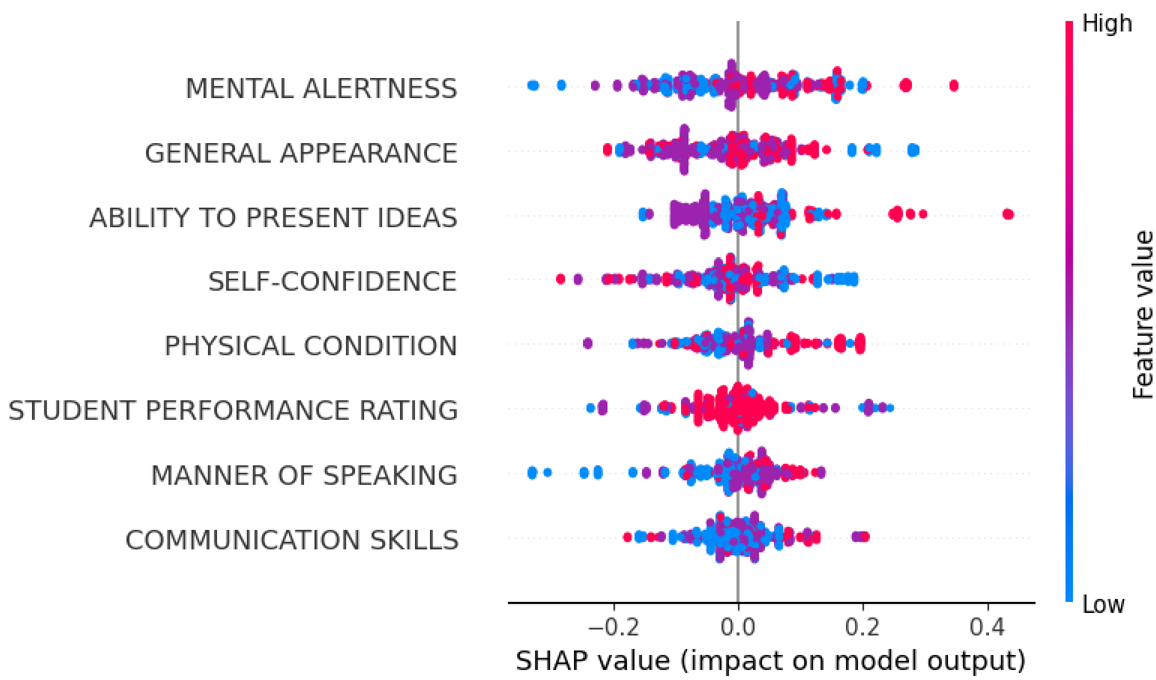

Figure 3. SHAP dot summary showing feature influence on student employability

The SHAP dot summary provides a detailed view of how individual feature values influence employability predictions in the Random Forest model. The results reveal that mental alertness is the most decisive factor, with higher values consistently driving predictions toward employability and lower values strongly contributing to the classification of students as less employable. This underscores the central role of cognitive sharpness and attentiveness in shaping employment readiness.

General appearance and the ability to present ideas also emerged as highly influential traits. Students who were highly rated in these areas were strongly associated with employability, while lower ratings increased the likelihood of being classified as less employable. These findings suggest that employers not only value intellectual ability but also place considerable importance on professional presentation and the capacity to communicate ideas effectively.

Similarly, self-confidence and physical condition exert meaningful influence, with higher values contributing positively to employability outcomes. Confidence, as a personal trait, appears to enhance perceptions of readiness and adaptability, while good physical condition reflects well-being and preparedness for workplace demands.

On the other hand, student performance ratings during on-the-job training (OJT), manner of speaking, and communication skills show relatively weaker but still consistent effects. Higher values in these attributes improve employability predictions, but their influence is less pronounced compared to cognitive and behavioral competencies. This indicates that while technical performance and communication style are important, they are secondary to traits such as alertness, professional demeanor, and confidence in determining employability.

On the other hand, Figure 4 shows the SHAP Dot summary, illustrating the feature's influence on lower employability. The SHAP dot summary highlights the conditions under which students are more likely to be predicted as less employable by the model. The results reveal that weaknesses across several traits consistently push the classification toward lower employability, with mental alertness standing out as the most decisive factor. Students who exhibit low attentiveness and limited cognitive responsiveness show strong negative SHAP values, clearly positioning them as at risk of being categorized as less employable.

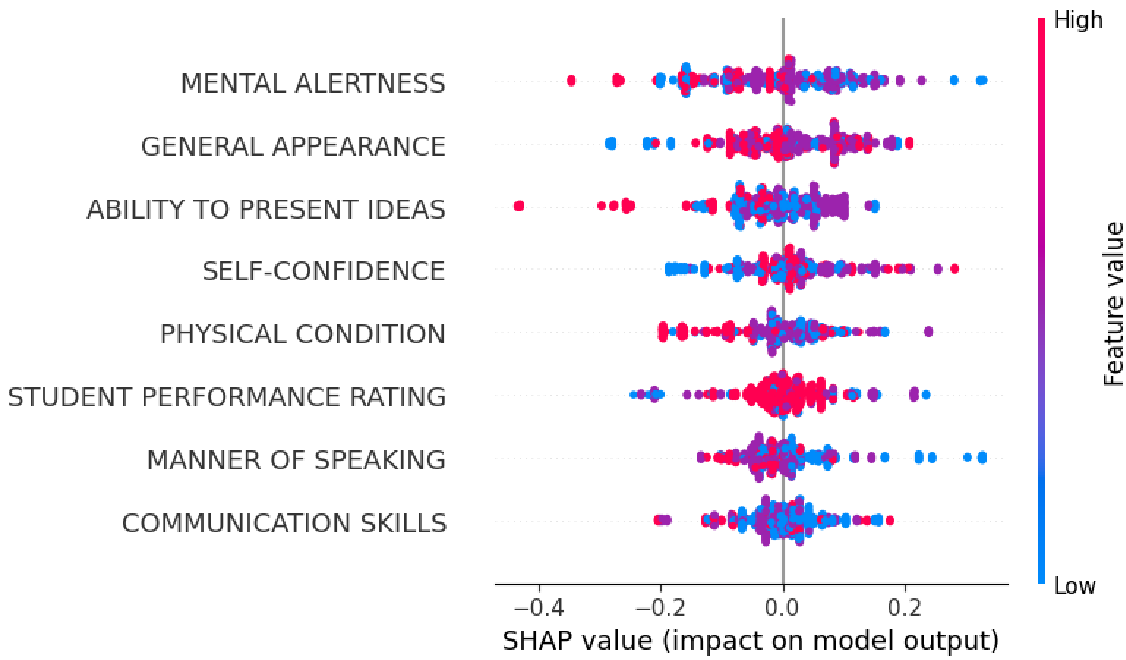

Figure 4. SHAP dot summary showing feature influence on lower employability

Another prominent contributor is general appearance, where lower ratings correspond to unfavorable employability outcomes. This suggests that students who fail to demonstrate a professional demeanor or present themselves adequately may be at a disadvantage in employability assessments. Likewise, the ability to present ideas clearly shows a distinct dividing line: students who struggle to articulate their thoughts or communicate coherently tend to be predicted as less employable.

Additional traits also weigh into negative classifications. Low self-confidence is consistently associated with reduced employability, indicating that uncertainty or hesitance diminishes perceptions of readiness for the workplace. Similarly, a weaker physical condition exerts a downward pull, suggesting that poor health or fitness may be perceived as a barrier to job performance. Although student performance during on-the-job training (OJT) has less influence compared to behavioral traits, unsatisfactory ratings nonetheless contribute to less favorable outcomes. Finally, deficiencies in manner of speaking and communication skills – while less impactful overall – still play a role in reinforcing predictions of lower employability.

Discussion

Understanding the factors that contribute to student employability is a critical concern for educational institutions, career counselors, and policymakers, particularly in the Philippine context, where bridging the gap between academic preparation and labor market demands remains a persistent challenge. This study addresses three interconnected research objectives: first, comparing and evaluating the performance of selected data mining and machine learning algorithms in predicting student employability based on measurable student attributes; second, identifying which student traits most significantly influence employability outcomes through the interpretation of SHAP values; and third, exploring how SHAP values can be leveraged to provide actionable insights for stakeholders seeking to design interventions that enhance career readiness. By situating predictive modeling and interpretable machine learning at the intersection of educational assessment and employability, the findings offer both methodological contributions and practical implications for evidence-based student development initiatives.

The Random Forest model demonstrated high predictive accuracy compared to SVM, KNN, and Logistic Regression, highlighting its potential as a reliable tool for identifying students who may require additional support to enhance employability outcomes. Previous studies have similarly shown the effectiveness of Random Forest in predicting student employability across multiple contexts. Baffa et al. (2023) reported that the Random Forest Classifier achieved an accuracy of 98% and an F1-score of 0.99 when using academic and experience-based attributes, with SIWES results emerging as the most important variable in distinguishing student employability. Vinutha and Yogisha (2021) further confirmed that Random Forest outperformed other machine learning models in predicting the employability of engineering graduates and identifying areas for improvement, providing actionable outputs such as eligibility reports for students and companies.

The algorithm has also been applied to assess the impact of entrepreneurship and innovation education, with Jia and Zhao (2022) demonstrating that an improved Random Forest model significantly enhanced the accuracy of evaluating talent development outcomes. Similarly, Prasad et al. (2023) identified key employability factors, including domain knowledge, problem-solving, computer skills, general awareness, teamwork, analytical thinking, and creativity. They showed that Random Forest effectively classified students based on these attributes, highlighting its applicability for targeted interventions. Collectively, these findings underscore the robustness of Random Forest as a predictive tool and its utility in guiding educators, career counselors, and program designers in developing evidence-based strategies to improve student employability, such as programs to strengthen communication skills, self-confidence, and the ability to present ideas effectively.

Interpretation through SHAP values revealed that employability is most strongly influenced by cognitive sharpness, professional appearance, and the ability to articulate ideas, while academic performance and technical skills contributed to a lesser degree. This finding highlights the importance of soft skills, personality traits, and cognitive readiness in shaping employability outcomes, surpassing the influence of purely academic achievements. Soft skills, including communication, leadership, teamwork, problem-solving, negotiation, and self-marketing, are widely recognized as essential for employability, complementing technical knowledge and supporting career development and workplace relevance (Subedi, 2018; Suneela, 2014; Tes & Khen, 2025). Cognitive functioning, particularly in areas such as attention, planning, reasoning, problem-solving, and verbal learning, has been linked to better employment outcomes and more favorable job placement, highlighting the importance of mental alertness and decision-making abilities for workplace success (Landolt et al., 2016; Lexén et al., 2016; Najib et al., 2024). Moreover, students' personality traits, especially agreeableness, conscientiousness, and openness, have been shown to positively influence self-perceived employability and align with career preferences, suggesting that individual differences in personality and cognitive appraisal can guide interventions aimed at preparing students for the labor market (Neneh, 2019; Ramirez et al., 2024). Taken together, these studies corroborate the current findings by demonstrating that holistic competencies, which blend soft skills, cognitive sharpness, and personal traits, play a central role in determining employability beyond traditional academic metrics.

The SHAP dot summary plot further reinforces that employability outcomes are driven primarily by mental alertness, professional presentation, and effective idea communication rather than academic measures alone. Students with higher scores in these areas were consistently classified as employable, whereas weaknesses increased the likelihood of being identified as less employable. These results align with industry perspectives that highlight holistic competencies, such as intellectual acuity, confidence, and interpersonal effectiveness, as key determinants of workplace success. Employers increasingly value competencies developed through work placements, internships, and extracurricular activities as indicators of job readiness, suggesting that graduates should document and highlight these skills through resumes or digital portfolios (Chan et al., 2024). While some studies note that employers prioritize employability skills such as communication, teamwork, and adaptability over broader holistic education attributes, elements like interdisciplinarity, self-reflection, and social responsibility remain relevant to overall workplace effectiveness (Santos et al., 2021). School-related factors, including quality instruction, engagement in research, and community extension programs, have also been shown to enhance graduates' holistic competencies and support employability outcomes (Dotong, 2014). Furthermore, personal competencies, such as communication, IT literacy, and foreign language skills, complement business competencies, enhancing graduates' competitiveness in the labor market and aligning academic preparation with employer expectations (Varga & Szira, 2020). Collectively, these findings underscore the importance of developing a combination of cognitive, interpersonal, and personal competencies to equip students to meet the multifaceted demands of the contemporary workplace.

In the Philippine context, the student traits identified as most influential reflect the intersection of local educational practices, workplace expectations, and cultural norms. Filipino employers often emphasize interpersonal skills, professionalism, and adaptability alongside technical knowledge, partly due to a workforce that values collaborative problem-solving and customer-oriented service (Acosta et al., 2017; Chan et al., 2024). Educational institutions in the Philippines traditionally focus on academic achievement. Yet, increasing attention is being given to experiential learning through internships, on-the-job training, and community engagement programs, which help students develop the soft skills highlighted in this study.

Furthermore, socio-cultural factors such as hierarchical organization structures, collectivist teamwork dynamics, and the importance of presentation and communication skills can amplify the impact of these traits on employability. Local policies, such as the K–12 curriculum reforms and government-supported technical and vocational programs, also aim to enhance employability by bridging the gaps between academic preparation and labor market needs. Together, these elements underscore that equipping Filipino graduates with both cognitive competencies and socioemotional skills is crucial for navigating the unique demands of the domestic labor market and enhancing the alignment between education and employment outcomes.

These findings underscore that student employability in the Philippine context is shaped by a combination of academic performance, cognitive abilities, soft skills, personality traits, and holistic competencies developed through practical experiences and personal growth. The Random Forest model, interpreted through SHAP values, offers a reliable and transparent approach for identifying the attributes most strongly associated with employability, providing actionable insights for educators, career counselors, and policymakers. By linking predictive modeling with evidence-based strategies for student development, this study highlights the value of integrating cognitive, interpersonal, and experiential learning opportunities to better prepare graduates for the complex and evolving demands of the labor market.

CONCLUSION

Addressing graduate employability in the Philippines requires bridging the persistent gap between academic preparation and the realities of labor market demands that affect genders in all forms. This study aimed to evaluate the predictive capacity of the selected variables in determining student employability, identify the most influential student traits based on SHAP values, and explore how these insights can inform stakeholders in designing interventions that enhance career readiness.

Among the models tested, including Random Forest, SVM, KNN, and Logistic Regression, the Random Forest classifier demonstrated the highest predictive performance, achieving a test accuracy of 92.2%, along with balanced precision, recall, and F1 Scores. Statistical comparisons confirmed that Random Forest significantly outperformed Logistic Regression and SVM, while its performance was comparable to that of KNN, establishing it as the most reliable model for distinguishing between employable and less employable students. These results highlight the robustness of Random Forest as a decision-support tool for higher education institutions, career development programs, and policy interventions.

SHAP-based interpretation further revealed that mental alertness, professional appearance, and the ability to present ideas were the most decisive traits influencing employability outcomes, with self-confidence, physical condition, and on-the-job training performance also contributing meaningfully. These findings underscore that employability extends beyond academic and technical proficiency, relying heavily on cognitive, behavioral, and soft-skill attributes.

Ultimately, this study demonstrates that integrating predictive analytics with interpretable machine learning and evidence-based insights provides a comprehensive approach for preparing students for a competitive and rapidly evolving labor market. By identifying key employability determinants and leveraging reliable predictive models, higher education institutions, educators, and policymakers can implement targeted interventions that enhance career readiness and support holistic student development.

RECOMMENDATIONS

Based on the findings, the following actionable recommendations are proposed:

1. *Curriculum Enhancement.* Higher education institutions should strengthen instructional strategies and review courses that develop communication, presentation, and interpersonal competencies. Where needed, a dedicated course or integrated activities across disciplines can ensure students continuously practice these skills in both academic and applied settings.
2. *Strengthened Experiential Learning.* Schools, in collaboration with host training establishments (HTEs), should expand internships, apprenticeships, and project-based learning opportunities to reinforce technical and behavioral competencies. Student training plans should be regularly updated to align with evolving workforce demands.
3. *Data-Driven Career Services.* Universities are encouraged to adopt software systems that integrate predictive modeling (e.g., Random Forest with SHAP) to monitor employability-related traits and identify students needing targeted support. Career services can then provide mentoring, workshops, and coaching tailored to individual skill gaps.
4. *Faculty Capacity-Building.* Educators should receive training to cultivate employability-related traits in the classroom, including confidence-building activities, structured peer evaluations, and assessments emphasizing professional presentation and workplace readiness.
5. *Continuous Employer Feedback.* Institutions should maintain regular communication with partner employers to identify skill gaps and co-design training modules that reflect evolving industry standards.

By acting on these recommendations, stakeholders can leverage data-driven insights to create a more responsive, inclusive, and future-ready education system that equips graduates with both technical expertise and the adaptive skills necessary to thrive in the workforce.

LIMITATIONS

This study excluded demographic variables to focus on measurable student traits, which may limit insights into employability equity. Manual oversampling was employed to balance class distributions, which may have impacted model robustness. The analysis relied solely on retrospective mock interview data, which may not fully reflect actual employment outcomes. These factors should be considered when generalizing the findings.

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AUTHOR

Cris Norman P. Olipas is an Assistant Professor of Information Technology at the Nueva Ecija University of Science and Technology, Cabanatuan City, Philippines. He holds a BS and MS in Information Technology, a Diploma in Social Studies Education, and a Doctor of Education in Industrial-Technological Education. A licensed professional teacher specializing in Social Studies, he is also completing an MA in Social Studies Education at the University of the Philippines Open University. His research focuses on social computing, social studies education, and information technology education, with interests in digital competencies, digital footprint awareness, and technology impact assessment.