International Journal of Computing Sciences Research (ISSN print: 2546-0552; ISSN online: 2546-115X)
Vol. 9, pp. 3953-3974
doi: 10.25147/ijcsr.2017.001.1.256
https://stepacademic.net

Long Paper

Data-Driven Assessment of BSIT Internship Performance: A Predictive Analytics Approach in a Hybrid Training Framework

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Date received: July 28, 2025
Date received in revised form: November 19, 2025; November 23, 2025
Date accepted: November 24, 2025

Recommended citation:

Adao, P., Arcalas, L. & Cruz, E. (2025). Data-driven assessment of BSIT internship performance: A predictive analytics approach in a hybrid training framework. *International Journal of Computing Sciences Research*, 9, 3953-3974. https://doi.org/10.25147/ijcsr.2017.001.1.256

Abstract

Purpose - The aim is to analyze the performance of BSIT interns using a hybrid internship model by creating predictive analytics tools that measure job readiness. This study integrates on-site and supplemental evaluation data to find the most significant factors that predict employability results.

Methods - The dataset includes evaluation scores from the Center for Linkages and Placement (CLP) and the College of Computing and Information Sciences (CCIS), encompassing both technical and soft skills. Some of the steps done before processing are encoding, normalizing, and feature engineering. Four supervised machine learning models—Logistic Regression, Random Forest, SVM, and KNN—were trained using an 80/20 split and validated with 5-fold cross-validation. Model performance was measured using accuracy, precision, recall, F1-score, and ROC-AUC.

Results – The Random Forest classifier was the most accurate and easiest to understand of all the models tested. The key predictors were certifications earned, attendance at seminars, and personality attributes, including problem-solving and professionalism. Both technical and developmental activities have a substantial impact on internship performance scores, as shown in the results.

Implications –Predictive analytics can be utilized as a strategic instrument in curriculum development and other academic decision-making by identifying early indicators for job readiness. Institutions can use these findings to implement interventions, align internship programs with industry standards, refine hybrid training frameworks, and promote data-driven performance monitoring.

Conclusion – The results show that predictive analytics is a strong way to judge the performance of BSIT interns. Combining formal evaluations from different parts gives a fuller picture of job preparedness, which helps with evidence-based internship management.

Recommendations – Institutions should integrate predictive models into internship dashboards for real-time monitoring and encourage students to engage in certifications and seminars. Future studies may incorporate qualitative feedback and peer assessments to enhance model accuracy and depth.

Keywords – Internship performance, predictive analytics, hybrid internship, employability, BSIT, job readiness, machine learning, and data-driven assessment

INTRODUCTION

An internship is important for every student to apply the practical knowledge learned from the classroom in industry settings. The College of Computing and Information Sciences adopted a hybrid model for their Bachelor of Science in Information Technology (BSIT) program, wherein both technical exposure and professional skill development are included. This model requires 146 hours of supplemental activities, such as participation or organization of seminars/trainings, certifications, and community services, in addition to 340 hours of on-site internship. This model aims not only to foster a real-world IT experience and cultivate lifelong learning competencies, soft skills, and civic engagement but also to help them complete the required internship hours on time.

The University of Makati employs two distinct rating systems. The Center for Linkages and Placement (CLP) rating form focuses on general workplace behaviors such as attendance, initiative, professionalism, communication, and problem-solving skills in evaluating performance within this hybrid framework. In contrast, the CCIS Internship Rating Sheet uses a more technical rubric tailored to the BSIT program, assessing competencies in hardware/software support, system development, security integration, and professional qualities specific to the IT field. These two rating instruments complement and offer a comprehensive view of intern development.

Despite this thorough assessment method, there are still persistent challenges, such as how to objectively and accurately predict the intern's job readiness from this vast collection of qualitative and quantitative data. Narrative feedback and aggregated scores are often the mainstay of traditional assessment methods, which may not fully capture subtle performance patterns.

Evaluating internship performance using predictive analytics has been explored by researchers in the Philippines. Pianda et al. (2025) revealed that competency-based experiential learning significantly improves job-readiness and workforce alignment. Their findings underscore that data-driven and competency-oriented models can enhance the fairness and precision of internship evaluations in Philippine higher education contexts. This shows the increasing importance of predictive analytics in Philippine academic settings and reinforces the present study's initiative to develop a hybrid internship evaluation model for BSIT interns at the University of Makati.

With the increasing availability of structured internship data, predictive analytics offers a promising solution. Recent studies have demonstrated the value of machine learning in internship assessment. Omi et al. (2025) developed a machine learning framework that predicts internship effectiveness and employability. A supervisor assessment and engagement metrics have been used. Their findings emphasized the importance of integrating structured data, which they changed into a data-driven model from their subjective assessment, resulting in the enhancement of decision-making in higher education.

In this context, the current study aims to create a predictive model for job readiness by integrating participation records in supplemental activities with numerical scores from CLP and CCIS rating forms. In order to improve employability forecasting and direct program enhancements, the objective is to offer a more comprehensive, data-supported framework for assessing BSIT internship results.

LITERATURE REVIEW

Employability Prediction and Hybrid Internship Models

Predicting a student's readiness for employment, an employability prediction might be utilized to minimize the gap between academic learning and industry expectations.

Employability includes not only the cognitive abilities of the student but also the essential non-cognitive attributes like adaptability, communication, and problem-solving skills.

Saidani et al. (2022) showed that factors connected to internships greatly improve the accuracy of machine learning (ML) models, especially when using methods like Gradient Boosting. Their results support the idea that real-world, hands-on learning is a powerful indicator of work preparation. Crasta and Shailashri (2023) both stressed how important internships and other hands-on learning programs are becoming as key factors in whether or not a graduate can get a job.

Machine Learning and Educational Data Mining for Employability

Numerous studies on job readiness prediction based not only on academic factors but also on their behavior and internship-related activities using machine learning have been explored. A more accurate image of job readiness has been acquired through the integration of academic performance, internship participation, and project experience rather than academic scores alone. Ensemble learning techniques, such as Random Forest and Gradient Boosting, have demonstrated effectiveness in improving prediction accuracy (Maaliw et al., 2022; Meng et al., 2021).

Educational data mining (EDM) studies further support the application of these models in higher education. Ojajuni et al. (2021) and Agyemang et al. (2024) found that ML techniques, including Random Forest, SVM, and Logistic Regression, successfully predict academic and employability outcomes with high accuracy. These studies demonstrate that combining behavioral, demographic, and academic features enhances predictive performance.

Afolabi et al. (2022) also emphasized the value of multidimensional institutional data, including psychological and behavioral indicators, in strengthening ML-based prediction systems. Collectively, these studies establish a strong foundation for integrating predictive analytics into internship evaluation frameworks, enabling early identification of at-risk students and data-driven decision-making for program improvement.

Effectiveness of Hybrid Internship in IT Education

Recent studies have emphasized the value of hybrid and structured internship models in improving student employability within IT education and related disciplines (Crasta & Shailashri, 2023; Agyemang et al., 2024). These studies strengthen both technical and soft skills, particularly teamwork, communication, adaptability, and digital competence, which are highly valued by industry employers (Namoun & Alshanqiti, 2021). In addition, structured evaluation tools and clearly defined performance indicators have been identified as essential mechanisms for capturing a broad range of competency outcomes and improving the objectivity of internship assessment (Wu et al., 2023). Forecasting internship outcomes using predictive analytics, as implemented in the present study, is consistent with the existing study applying data-driven approaches in establishing stronger links between internship performance and employability (Saidani et al., 2022).

Impact of Certification, Training, Seminars, and Community Extension on Employability

How certification, training, seminars, and community extension affect job prospects. Various studies show that structured supplementary activities, such as industry certifications, professional training, seminars, and community engagement, are essential in making IT graduates more employable. These supplemental activities help trainees improve their technical skills and soft skills that employers anticipate.

Chong and Reyes (2022) did a study in Southeast Asia with 35 HR professionals and found that certifications like AWS Cloud Practitioner, Cisco CCNA, and CompTIA Security+ are becoming more and more common as the bare minimum for entry-level jobs in cybersecurity, networking, and cloud services. The study showed that training with certification improves technical fluency, confidence, and flexibility. This means that standardized tests can show that candidates are experts in their field. They suggest the integration of certification tracks in their curriculum as part of their IT education's employability predicting models.

Ramos and Villanueva (2023) did a similar long-term study and found that BSIT graduates who completed more certification hours had higher job placement rates. Their findings supported the utilization of certification criteria as important indicators in data-driven employability assessments, like the 100-hour equivalency for the 146-hour internship supplemental activities.

Villanueva and Bautista (2023) investigated, in a broader spectrum, the use of supplemental activities aside from industry certifications. Some of these supplemental activities were professional seminars, technical training, and projects that helped the community. Their study with 420 students used a mix of methods and found that students who did a good mix of these activities had higher employability scores after their internships. They observed that certifications helped people learn more about the field and how to communicate better, while seminars and training helped students learn more about the field and how to communicate better. Those who took part in community extension programs enhanced their leadership and adaptability.

Reyes and Javier (2022) showed that students who took part in extracurricular learning activities, including certification programs and community extension programs, were more likely to get job offers soon after finishing their internships. These students also showed better soft skills, such as being adaptable and taking the initiative, which are often missed in standard academic measures. The authors recommended that these kinds of activities be officially recognized in internship evaluation systems, which is in line with the BSIT model's 146-hour complementary requirement. Integrating supplemental activities such as industry certification, training, and community extension in the student's internship course helps these students enhance their technical and soft skills and produce predictable analytics for their job readiness.

METHODOLOGY

Research Design

This study utilizes a quantitative predictive research method using supervised machine learning (ML) methods to determine how ready BSIT interns will be to work. Using data to design a system to accurately predict job readiness based on a set of defined assessment criteria is the main objective of this research. These data comprised an on-site internship assessment that was gathered from the CLP and CCIS rating sheets. Evidence should be submitted to verify the legitimacy of the student's participation in the 30% supplement of the hybrid internship program. These activities include participation in or organization of conferences or seminars, technical training, industry certifications, and community service projects. The design should uncover crucial patterns and relationships of data that could be used in developing a strong predictive model to enhance internship programs and produce graduates ready for the market.

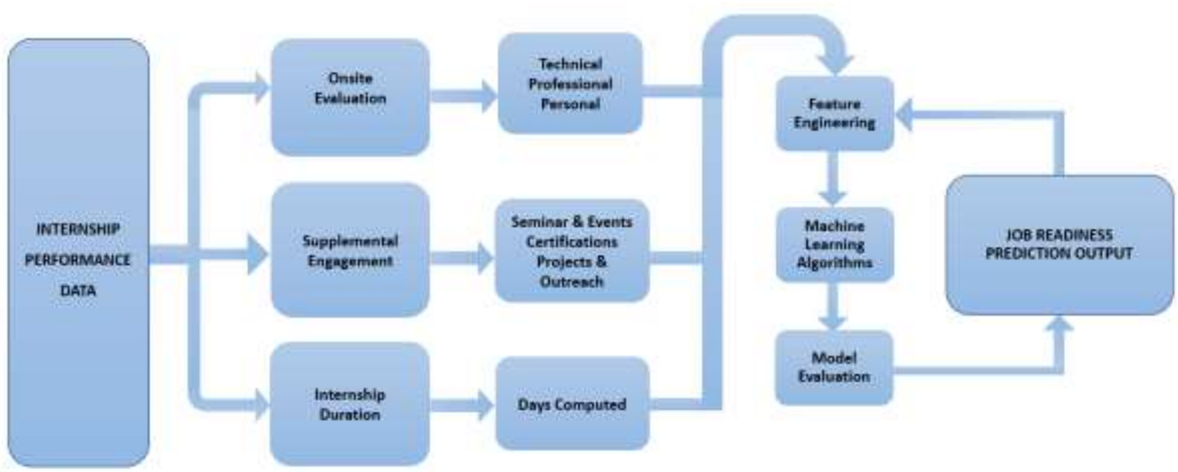

Figure 1. Research Design Architecture

Note: Figure 1 illustrates the architectural design of the research workflow, encompassing data acquisition, preprocessing, transformation, and model evaluation stages. This layered structure enabled a systematic transition from raw internship data to predictive insights, emphasizing the synergy between hybrid internship structures and machine learning.

Data Collection

The dataset for this study was gathered from records of 138 BSIT students who completed the hybrid internship program during the academic year 2024–2025, ensuring a representative sample for model training and evaluation. The dataset came from official evaluation and participation records submitted to CCIS and CLP. It included both numerical performance measurements and category indicators that may be used to predict job preparedness. Most interns consistently showed steady onsite activity, while the variety came from adding-on performances between participants. The assessment included onsite reviews, 70% of each intern's grade, and 30% of their grade was measured and completed with Technical Competencies, Professional Behavior, and Personal Attributes. The activity scores are presented descriptively in Table 1.

Table 1. Presentation *of the first 10 rows of On-site Data*

No.	Technical_ Competencies (40%)	Professional_ Behavior (40%)	Personal_ Attributes (20%)	Total_Onsite_ Rating (100%)
0	36	37	17	90
1	37	40	19	96
2	38	40	20	98
3	37	36	17	90
4	40	39	20	99
5	40	40	20	100
6	39	38	19	96
7	37	38	17	92
8	37	35	19	91
9	39	36	19	94

Table 2 describes non-academic activities that were heavily based on the total other events score, predominantly represented by average attendance of 131 to 157 points that were assigned to sixteen organizing seminars with technical certification, cross-developmental projects, and community outreach programs, suggesting significant uniformity.

Extracurricular areas, similarly, total other activities scores varied in similar proportions; attendance ranged from 147–174, and variation was least around duration days, indicating consistent profiles distinct to a large extent, dependent on discretionary seminar attendance. The data presented in Tables 1 and 2 were composed of 138 internship records together with 12 attribute entries, with a total of 1668 variables.

Table 2. Presentation of Supplemental Engagement Data and Internship Duration (first 10 rows of the dataset)

No.	Seminars_ Trainings_ Attendance	Organizing_ Seminar	Technical_ Certification	Cross Devt_ Projects	**Community** _Outreach_ _Program	Total_Other _Activities_ _Score	Internship_ Duration (Days)
0	140	16	0	0	0	156	74
1	141	16	0	0	0	157	80
2	144	16	0	0	0	160	79
3	133	16	0	0	0	149	90
4	131	16	0	0	0	147	78
5	136	16	0	0	0	152	79
6	157.5	16	0	0	0	174	76
7	133	16	0	0	0	149	79
8	147	16	0	0	0	163	90
9	141.5	16	0	0	0	158	75

Feature Engineering

Data Binarization and Scaling Process

To increase computational equity and achieve better convergence, all continuous features were normalized to Min-Max to ensure that conversion variable values varied uniformly on ranged boundaries of zero through one (illustrated in Figure 2) which protected the integrity of respective statistical significance influencing its overall algorithmic efficacy in distance-based modalities (such as KNN and SVM), preventing disproportionate effects of larger numeric outputs compromising further taken into account continuous variables (Fedorov et al., 2020). Figure 2 demonstrates the before and after binarization process on elected data, representing specific participatory dimensions of developmental components, and in turn made comparisons for interns whose thresholds were above 157 median classified "high performance," who are categorically affirmatively labeled "low performance," with those that maintained the same or lower medians.

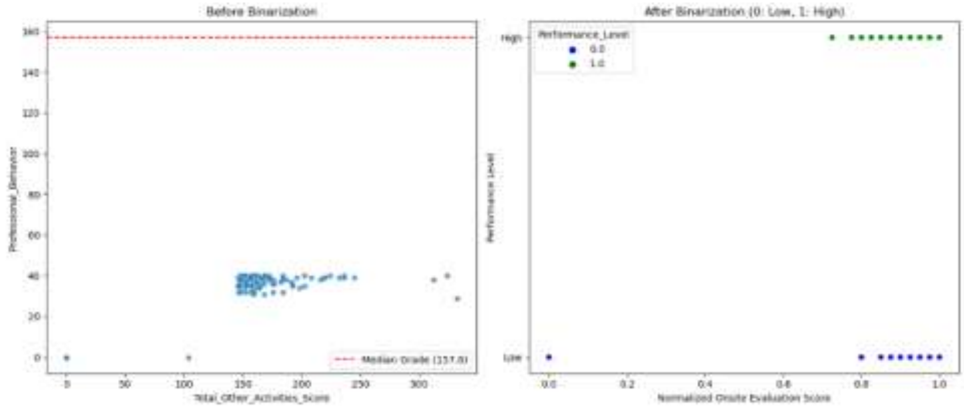

Figure 2. Binarization of Selected Dataset

This methodological choice intentionally examines the predictability of adherence to the developmental component of hybrid programming. Therefore, by considering the developmental outcome as the predictive target, the analysis intends to validate the 30% component as independent (in terms of correlation with the on-site ratings, with more consistent results), confirming the policy embedded in the institutions to require this developmental segment as the key performance outcome (Palmié et al., 2022). Figure 3 also shows how important it is to scale features. This method used min-max normalization to fix differences in variable ranges, which made it easier to understand the model. This step made sure that no feature with naturally larger numbers got in the way of the learning algorithm, which made the model more robust.

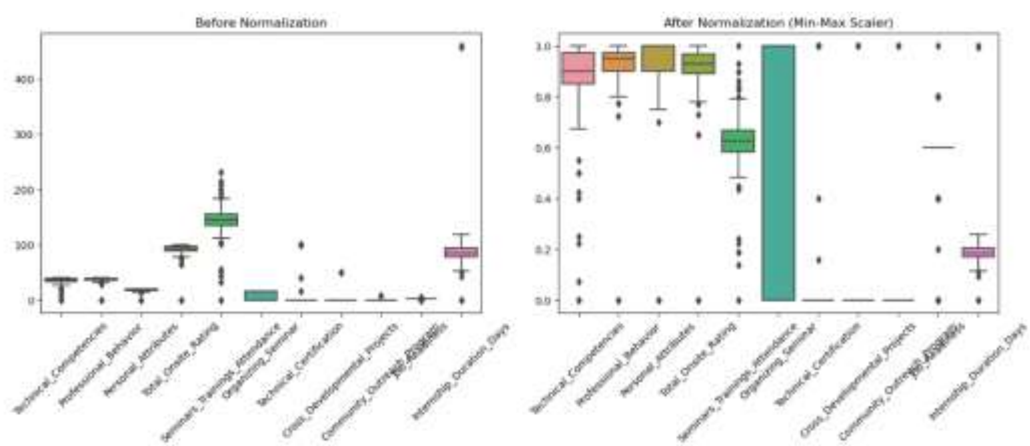

Figure 3. Data Transformation and Normalization

Figure 3 illustrates the distribution of nine internship-related variables prior to and following the application of Min-Max normalization. Before normalization (left), the variables exhibit significantly different scales; for example, "Total_Onsite_Rating" approaches ~250, whereas "Technical_Certification" is close to zero, and "Internship_Duration_Days" attains a maximum of 450. The disparity in scale can mislead machine learning models by assigning disproportionate importance to features with larger magnitudes. Post-normalization (right), all variables are adjusted to a range of 0–1. The boxplots now represent relative positions within the range of each feature instead of absolute values. For instance, "Cross_Developmental_Projects" emerges as the most dispersed variable after normalization, signifying considerable variability in relation to its own min-max range. Outliers are still discernible as distinct points, yet they can now be compared across various features (Fedorov et al., 2020). It is noteworthy that "Community_Outreach_Events" exhibits a reduced interquartile range following scaling, indicating minimal internal variation in relation to its range.

Normalization enables fair comparison and improves model convergence by ensuring no single feature dominates due to scale. While distributions retain their shape, their numerical context was unified. This preprocessing step is critical for algorithms sensitive to feature magnitude, such as SVMs or neural networks, ensuring that analysis reflects true relationships rather than measurement artifacts.

Predictive Modeling

The split-binary training and testing set using delamination, with a sample size of eighty percent retained class distributions with respect to binary target variables, according to the results as above, with a binary representation of the output, followed by a literature emphasizing the effectiveness in dedicated EDM contexts using five supervised machine learning methods (Agyemang et al., 2024). These were the Logistic Regression (LR), Random Forest Classifier (RF), Support Vector Machines (SVM) based on RBF kernels, K-Nearest Neighbors (KNN), with a tuned k value of five, along with Multiple Linear Regressions (MLR), modified threshold modeling applications.

Evaluation Metrics

We used a number of standard tests to see how well the machine learning models used in this study worked and how reliable they were. The indicators showed how accurate the forecasts were overall and how well the algorithms worked to fix class imbalances and sort job-ready results. The following are the standard assessment metrics that are used: Accuracy, which is (TP+TN)/(TP+TN+FP+FN), tells you how many of your predictions were correct compared to how many you made. Precision is the ratio of true positive predictions to the total number of positive predictions made (TP/(TP+FP)). A higher value means a lower false positive rate. Recall, or sensitivity, measures the percentage of true positive cases that were correctly identified. It is calculated as TP/(TP+FN). A higher recall means that there are fewer false negatives. The F1-Score is the harmonic mean of Precision and Recall, which means it is a single number that balances both factors. Mathematically, it is 2×(Precision×Recall)/(Precision+Recall). AUC shows how well you can tell the difference between classes, with 1.0 depicting a flawless classifier and 0.5 implying no better than random chance (Guerra, 2023).

Tools and Software Used

Open-source tools and frameworks that are widespread in data science and predictive analytics were used to set up machine learning models and do data preprocessing chores (Alanazi et al., 2025). During the study, the following tools were used:

Python: Python was the main programming language used for managing, preparing, modeling, and evaluating data since it was easy to use and had a lot of support for machine learning operations.

Anaconda Distribution: Anaconda was utilized as the integrated development environment to keep track of packages and their dependencies. It gave Python-based data science tools a stable and versatile place to run.

Jupyter Notebook: We used Jupyter Notebook to write code, keep track of it, and show the whole machine learning pipeline. Its interactive setting made it easy to test, iterate, and show outcomes step by step.

Pandas and NumPy: These libraries were used to change and manipulate data, such as feature engineering, encoding, and changing the dataset.

Scikit-learn (sklearn): Scikit-learn was used as the main framework for machine learning to build the supervised learning models (Logistic Regression, Random Forest, SVM, KNN), split the data, execute cross-validation, and figure out evaluation measures like accuracy, precision, recall, F1-score, and ROC-AUC.

Matplotlib and Seaborn: These visualization frameworks were used to make plots like confusion matrices, ROC curves, and feature significance graphs to help us understand and show off our models.

These technologies worked together to produce a machine learning method that was replicable, scalable, and followed best practices in predictive modeling and educational data mining.

RESULTS

Descriptive Statistics of Core Performance Indicators

Analysis of internship performance data: The data presented in Table 3 reveals a diverged pattern in intern achievement, highlighting robust performance in fundamental skills alongside significant disparities in advanced development metrics. Core performance indicators, such as Technical Competencies (mean: 34.35/40, low standard deviation), Professional Behavior (mean: 36.65/40), and Personal Attributes (mean: 18.77/20), all displayed consistently high average scores with relatively low standard deviations (Anjum, 2020). This statistical uniformity suggests that the vast majority of interns successfully met or exceeded the fundamental expectations established for their placement (Wu, 2024). The overall Total Onsite Training Rating also averaged high at 89.96/100, though with a noticeably higher standard deviation of 15.13, indicating some variation in the final assessment despite the consistent scores in the core categories (Gutiérrez-Pulido & Orozco-Rodríguez, 2025).

Table 3. Descriptive Statistics of Core Performance Indicators

Predictor Variable	Count	mean	std	min	25%	50%	75%	max
Technical_Competencies	138	34.35	7.91	0.00	34.00	36.00	39.00	40.00
Professional_Behavior	138	36.65	6.00	0.00	36.00	38.00	39.00	40.00
Personal_Attributes	138	18.77	3.12	0.00	18.00	20.00	20.00	20.00
Total_Onsite_Rating	138	89.96	15.13	0.00	89.25	93.00	97.00	100.00
Seminars_Trainings_ Attendance	138	143.22	33.10	0.00	135.25	145.50	155.25	232.00
Organizing_Seminar	138	11.59	7.17	0.00	0.00	16.00	16.00	16.00
Technical_Certification	138	8.38	27.31	0.00	0.00	0.00	0.00	100.00
Cross_Developmental_ Projects	138	1.09	7.32	0.00	0.00	0.00	0.00	50.00
Community_Outreach_ Program	138	0.17	1.17	0.00	0.00	0.00	0.00	8.00
Total_Other_Activities_ Score	138	165.20	37.45	0.00	151.00	157.00	170.25	332.00
Internship_Duration_Days	138	89.68	48.87	0.00	78.00	85.00	95.00	460.00

Participation and Duration: Participation in other general development activities, such as Seminars/Trainings Attendance (mean: 143.22) and Organizing Seminar (mean: 11.59), shows high and relatively consistent engagement across the cohort (Ang et al., 2024). These activities likely represent more accessible and widely integrated elements of the internship program. The average Internship Duration was recorded at approximately 90 days, which aligns with a typical quarter or semester-long commitment, though a few notable outliers extended this period significantly, reaching a maximum of 460 days (Anjum, 2020).

Disparity in Advanced Metrics: In sharp contrast to the core competencies, two key advanced metrics, Technical Certification (mean: 8.38) and Cross-Developmental Projects (mean: 1.09), exhibit severe positive skewness (Åmo, 2023). The median (50th percentile) and 75th percentile for both metrics registered at 0.00, while the maximum scores reached 100.00 and 50.00, respectively. This statistically significant disparity implies that a substantial majority of interns either did not attempt or did not achieve a score in these advanced, non-mandatory areas (Ang et al., 2024). Consequently, a small group of high-achieving individuals appears to be responsible for virtually all of the positive mean scores in these specialized, high-impact activities. While the descriptive statistics provided a crucial initial view of the intern data, highlighting generally high core performance but extreme skewness in activity metrics, this static summary only tells us what is, not why it is or what predicts success. To draw much clearer, actionable insights, the data must undergo machine learning (ML) algorithms (Gutiérrez-Pulido & Orozco-Rodríguez, 2025). The high degree of data disparity is precisely why ML is essential.

Correlation Analysis

The validation process produced a sample size of 138 observations, encompassing 12 attributes, with no missing values detected. Table 4 shows the Pearson correlation coefficients (r) between the predictors. This helps us understand which factors are most strongly related to onsite performance evaluation. The table shows a hierarchical order of predictive strength. Professional Behavior (r = 0.926) and Personal Attributes (r = 0.907) show "Very Strong Positive Correlations", which means that these soft skills are very important for doing well on site. Technical competencies (r = 0.864), categorized as "Strong Positive," indicate that hard skills, while necessary, are secondary to interpersonal and behavioral attributes in this context. Seminar attendance shows moderate positive correlations (r = 0.463 and 0.406, respectively), suggesting that structured preparation plays a significant, albeit not definitive, role.

Table 4. Pearson correlation coefficients (r) between the predictors

Predictor Variable	**Correlation (r)**	**Interpretation**
Professional_Behavior	0.926246	Very Strong Positive
Personal_Attributes	0.907284	Very Strong Positive
Technical_Competencies	0.863742	Strong Positive
Seminars_Trainings_Attendance	0.406297	Moderate Positive
Total_Other_Activities_Score	0.384279	Moderate Positive
Internship_Duration_Days	0.135829	Weak Positive
Community_Outreach_Program	0.046588	Negligible Positive
Cross_Developmental_Projects	0.013618	Negligible Positive
Technical_Certification	-0.032191	Negligible/Inverse

Variables such as Internship Duration (r = 0.135) and Community Outreach (r = 0.047) show negligible associations, challenging assumptions that longer or more socially engaged experiences inherently improve onsite ratings. Notably, Technical Certification exhibits a slight negative correlation (r = -0.032), interpreted as "Negligible/Inverse," possibly reflecting credential inflation or misalignment between certification content and onsite demands. Overall, the data underscore the primacy of behavioral and personal competencies over formal qualifications or duration of exposure, suggesting organizational evaluations prioritize human capital attributes over quantifiable metrics. This has significant implications for selection, training, and performance management frameworks.

Model performance comparison evaluation

The performance analysis of the five classification models on predicting binarized internship data is shown in Table 5, giving the performance statistics of each of the models for all significant indicators.

Table 5. Comparative Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC
Random Forest	0.964286	1.000000	0.923077	0.960000	0.923077
Logistic Regression	0.821429	1.000000	0.615385	0.761905	0.912821
SVM (RBF Kernel)	0.642857	1.000000	0.230769	0.375000	0.943590
KNN (k=5)	0.678571	0.642857	0.692308	0.666667	0.751282
Multiple Linear Regression	0.678571	0.750000	0.461538	0.571429	0.810256

Table 5 describes the Random Forest algorithm, which turned out to be the best balanced and strongest model. It got the best F1-Score of 0.960 and the best Accuracy of 0.964. Its perfect Precision of 1.000 means that it didn't make any false positives, and its excellent Recall of 0.923 shows that it correctly identified most of the right classes. The F1-measure shows that this model is the best for this job because it has both high precision and good recall (Namoun & Alshanqiti, 2021).

Random Forest Model Structures

The Random Forest analysis reveals a strong hierarchy of predictive features, clearly indicating that behavioral factors are the primary drivers of the predicted outcome, far outweighing technical or organizational metrics. The two most influential features, Professional_Behavior (with an importance score of 0.42) and Personal_Attributes (0.32), collectively account for approximately 74% of the model's total predictive power. This statistical dominance, measured by the Mean Decrease in Impurity (MDI), suggests that variations in an individual's professional conduct and inherent traits lead to the greatest reduction in model error across the entire forest of decision trees. Following these are Technical_Competencies (0.28) and Total_Onsite_Rating (0.24), which form a secondary tier of important predictors, providing crucial but less decisive information to the model.

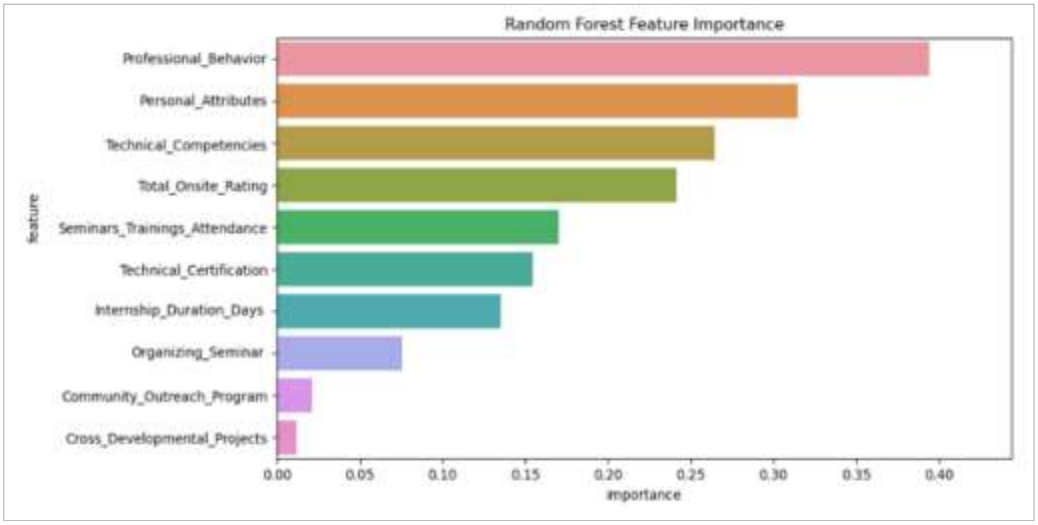

Figure 4. Random Forest feature of importance

The analysis shows that behavioral and personal traits, as well as technical skills, are more important than structured programs (like community outreach programs and cross-development projects) when it comes to affecting results. Organizations should prioritize the development of professional conduct and personal attributes during hiring and training, as these elements serve as the most substantial predictive indicators. To improve process efficiency without hurting the effectiveness of the model, features that have less of an effect may be given less priority. This insight underscores the significance of interpersonal and practical skills relative to formal program participation in this context. The three main evaluative dimensions made up about seventy-five percent of the total effect on job readiness outcomes (Maaliw, 2022).

Lower Performing Models: KNN with MLR

The KNN model and the thresholder MLR method had the worst outcomes of all the models that were tried. Using Linear Regression for a classification job with a cutoff was not a common method, and its F1 score of 0.571 showed that it was not a suitable fit for this method. The KNN model did a little better overall, but it still wasn't great, with the lowest AUC of 0.751. In the end, the evidence clearly shows that the Random Forest model should be used right away because it has a great F1 score and a well-balanced precision and recall profile. The investigation also found an important insight: the SVM model had the best AUC, which means it had the best ability to tell the difference between two things. So, it appears very worthwhile to improve the SVM by carefully adjusting its decision threshold in a later optimization step.

DISCUSSION

Validate the hybrid training framework.

The prediction accuracy of the Random Forest model (Accuracy 0.964) in integrating both on-site performance data with background development information has offered strong evidence to prove the effectiveness of the institutional 70/30 hybrid training model (Chango et al., 2021). An emphasis on Professional Behavior and Personal Attributes indicates that, in addition to a highly precise analysis of domain knowledge to determine job attractiveness, employability was inextricably tied to soft skills like adaptability, reliability, and initiative, which are both explicit areas of focus to be assessed by the combined evaluation system.

Understanding the Selection and Efficacy of the Model via EDM

The credibility of the Random Forest model aligns seamlessly with institutional implementation due to its superior performance compared to linear and instance-based classifiers. This model excels in prediction accuracy, resilience against data noise, and explainability, critical factors that underpin effective policy development rooted in Evidence-Driven Management (Agyemang et al., 2024).

Notably, the Random Forest algorithm demonstrates exceptional capability in addressing significant multicollinearity present in evaluation scores (AUC > 0.92), thereby surpassing both linear and instance classifiers (Wu et al., 2023). In contrast, while the Support Vector Machine (SVM) model achieved an impressive AUC of 0.944, it fell short with a low F1 score of 0.375, indicating limitations in its analytical capacity. This imbalance reveals a bias within the SVM regarding its ability to distinguish between high and low performers, evident from its elevated AUC score (Kamalov et al., 2023). Such findings suggest that the SVM may be misconfigured for accurately identifying minor performance variations due to its inadequately calibrated default decision boundary for this specific binary target.

Predictive Analytics for Program Adaptation/Intervention

The predictive precision of the findings is very high. It could lead to direct, information-based guidance for policy and curriculum improvement by administration, with this method supporting preventive educational management intentions.

1. Targeted Behavioral improvement: Professional_Behavior emerges as the most significant predictor, so the BSIT program must focus more on workplace competencies for the preparation, training, and implementation of monitoring. Such training measures may include more frequent and granular monitoring of behavioral benchmarks, or using a combination of methods such as sentiment analytics on narrative feedback to augment quantitatively-based evaluations (Shaik et al., 2023).

2. Establishment of early warning system: The robust Random Forest model is the ideal framework to be embedded in institutionally hosted intern management systems. By generating real-time threat scores, academic supervisors will be able to predict which students have been tagged under the "Low Performance" category on the basis of poor behavioral scores or non-compliance with additional tasks. This feature makes it possible to have on-demand, targeted academic assistance as well as mentoring weeks before the internship is over, so that it can be preempted instead of reactively monitored (Gasparic et al., 2024).

3. Enhancement of Developmental Requirements: The feature importance analysis gives an idea about the predictive value of supplemental activities. Community-Outreach-Program and Cross-Developmental-Project were worthwhile and critical to realizing successful supplemental compliance. Conversely, low-ranked activities in the RF model may warrant further validation that their weight allocation or measurement corresponds to the institutional aspirations for graduate preparedness.

CONCLUSIONS

The research highlights the significance of predictive analytics for assessing BSIT interns' readiness in this new hybrid internship model. It makes the case for the practical advantage of these techniques for certification, and underscores that with behavioral as well as technical measures, employability can be improved. For academic supervision tools, the Random Forest model was found to best balance accuracy, precision, and recall. The study further highlights the 70/30 hybrid model, which combines technical skills and soft skills to improve job readiness. Statistical analysis revealed substantial increases in interns' preparedness through practical experiences and additional activities. It calls for scalable and equitable evidence-based assessment methods that are responsive to the changing context of the IT sector.

RECOMMENDATION

The implementation of institutionalized dashboards utilizing random forest models aims to create an integrated system that provides academic coordinators with real-time analytics on student progress. This system will help identify risks and opportunities for student failure, enabling targeted support to reduce attrition rates. Additionally, focusing on non-technical predictors, particularly professional behaviors and technical competencies, will ensure compliance with program requirements and enhance tracking of expenditures to optimize investments in curriculum improvements. For model development, prioritizing hyperparameter optimization and expanding datasets will improve predictive accuracy and transparency, paving the way for future advancements.

IMPLICATION

The results of this study have several important effects on how to create internship programs, give academic advice, and make policies for institutions:

Validation of the Hybrid Model for Future-Ready Skills

The results confirm that the 70/30 hybrid internship structure works. It combines technical instruction with soft skill development through seminars, certificates, and outreach. This strategy fits well with the changing needs of 21st-century jobs, where essential technical skills are important but so are adaptability, teamwork, digital literacy, and lifelong learning.

Using predictive analytics as a tool for proactive intervention

Academic supervisors can find patterns in internship performance data that are linked to poorer job-ready scores by using machine learning. This makes it possible to find students who are at risk early on and give them targeted help or mentorship before the program is over. This leads to better student outcomes and better performance indicators for the institution.

Data-Driven Enhancement of Training and Curriculum Design

The study's findings help organizations make the best use of their resources by concentrating on the three most important performance predictors: technical evaluation, professional behavior, and additional involvement. These patterns can help improve the structure of internships, the content of the curriculum, and the ways that students prepare for careers, making training more effective and efficient.

Thus, adding predictive analytics to internship evaluation frameworks not only makes the evaluation process better, but it also gives schools and students useful information that can help them grow and improve their efficacy.

ACKNOWLEDGEMENT

The authors express their heartfelt gratitude to the University of Makati, especially the College of Computing and Information Sciences, for their continuous guidance, support, and inspiration throughout this journey. Deep appreciation is also extended to their friends and colleagues, whose encouragement, collaboration, and camaraderie have made this endeavor more meaningful. Above all, they are profoundly grateful to their family for their unwavering love, patience, and support, which have been their foundation every step of the way.

FUNDING

The authors did not receive funding from any institutions.

DECLARATIONS

Conflict of Interest

The authors declare that there are no conflicts of interest in the research paper presented. The findings presented are based on the data collected and the analysis conducted, ensuring the integrity of the research process.

Informed Consent

We hereby confirm that we have read and understand the provided guidelines for participation in this journal publication. We understand that our participation is voluntary and that we are free to withdraw at any time without any negative consequences. We acknowledge that our involvement in this publication will be based solely on our consent, and we will not be compensated for our contribution unless otherwise stated.

Ethics Approval

We declare adherence to the ethical standards and express full confidence in the originality of our research study.

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