

APPLYING Machine Learning in Predicting Probable Senior High School Strand Basis for Career PLANNING

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ABSTRACT

Three popular algorithms were considered to create the Strand Prediction System: the Naïve Bayes, Deep Neural Network, and Random Forests. The three algorithms in terms of accuracy were DNN (84.70%), Random Forest (95.25%), and Naïve Bayes (52.9%). Random Forest's ensemble technique ensured consistent and reliable performance while reducing overfitting. To enhance the dataset for the model creation, the SMOTE (Synthetic Minority Over-sampling Technique) was used to balance the distribution of the strand instances, thereby creating an acceptable dataset, which was used in the WEKA application to create the models. By doing so, the accuracy rate was increased. The system prototype passed all the tests, and the high average score of 4.56 shows that users think it is valuable and easy to use. To top it all off, it was well-received. However, issues with the results' demonstrability revealed areas that may be improved. The researcher secured the authorities' approval before collecting data from different schools and administering the adopted TAM2 survey questionnaire.

KEYWORDS: *Education, information technology, data mining, machine learning, classification algorithms, Philippines*

INTRODUCTION

As education systems evolve to meet the diverse needs of students, educators increasingly emphasize personalized learning pathways. One example is the selection of academic strands in senior high school, which strongly influences students' future educational and career trajectories. High school seniors often face challenges during the strand selection process as they try to choose majors that align with their interests and aspirations. Further, Bilecen and

Van Mol (2017) revealed that many students, guided by friends and family, select strands that mismatch their capabilities, negatively impacting their academic performance, while Smith (2002) revealed that students lack sufficient knowledge about academic options and rely on peer advice rather than trained counselors. Furthermore, Wang and Degol (2013) noted that students from lower socioeconomic backgrounds often rush into vocational training because of financial constraints. Although career counseling programs aim to align interests with job market demands, Beggs et al. (2008) highlighted that students often select majors based on personal preference, which results in job-hopping and unemployment risks, as Fan and DeVaro (2020) pointed out. Moreover, Anderson and Denley (2014) showed that predictive analytics improves strand choices' relevance, making them 25 percent more suited to students' interests and needs.

More so, strand selection among high school students presents significant challenges worldwide, as many struggle to align their academic choices with their interests and career aspirations. Researchers have found that students heavily rely on informal networks, such as friends and family, to guide their strand selection. Additionally, Gottfried et al. (2017) reported that this reliance often leads to a mismatch between students' chosen paths and their actual capabilities in California. Similarly, Gordon and Steele (2020) revealed that students across states frequently enroll in strands unsuited to their strengths, negatively affecting their academic performance and future career prospects.

Similarly, Li et al. (202) used Deep Neural Networks (DNN) models to accurately predict the academic paths students would choose for their future careers, which improved educational counseling practices in European high schools. Additionally, Kumbhar et al. (2023) showed that RNN models, by capturing intricate patterns in students' vocational inclinations, assist high school students in India in making optimal significant choices. Moreover, Catedrilla et al. (2022) conducted a study in the Davao region using machine learning algorithms to analyze student data, including academic performance and personal interests, to predict suitable strands for high school students. The researchers leveraged historical data to develop a predictive model highlighting key factors influencing students' success. In the same way, Nazareno et al.'s (2019) findings revealed that external pressures and limited access to career counseling services often challenged students, preventing them from choosing appropriate strands.

Notably, several studies have investigated career guidance and strand

selection for senior high school students. However, researchers have yet to develop and implement a machine learning-based strand prediction model tailored explicitly to Tacurong City's educational context. Noteworthy to know that Smith (2002), Beggs et al. (2008), and Fan and DeVaro (2020) examined general factors influencing strand selection.

However, they did not apply data-driven approaches like machine learning to predict suitable academic paths. Similarly, studies by Quintos and Caballes (2020) and Werblow et al. (2013) focused on regions such as Metro Manila and California, limiting their applicability to Tacurong. Although Catedrilla et al. (2022) and Nazareno et al. (2019) explored predictive models using data mining and decision-making techniques, none created a machine-learning model for Tacurong's senior high school students. This gap underscores the need for a machine-learning system that analyzes Tacurong-specific student data. This tool would enable counselors and administrators to guide students toward more informed decisions aligned with their interests and aspirations, ultimately improving educational outcomes and career alignment.

This research aimed to use data mining and machine learning to create strand selection software for senior high school students, generating significant societal benefits by promoting equity and inclusion. This research can potentially enhance educational outcomes and increase student satisfaction, fostering a more competent, workforce-ready generation. By applying data mining and machine learning techniques, educators and schools can gain valuable insights, refine curricula, and improve support systems to address students' needs better. These advancements ultimately promote social equity and contribute to long-term economic stability.

METHODS

Research Design

This study utilized a quantitative approach to explore variables methodologically, employing statistical tools for meaningful data analysis. Descriptive research was chosen to identify patterns and trends among students, leveraging Creswell's (2014) and Babbie's (2020) frameworks. Data collection involved manually copying student records from the registrar's office and encoding them into a .xls file, with academic performance data as the foundation for model creation. TAM2-adopted surveys were also employed to gather feedback from school stakeholders using the application. Descriptive statistics

and data mining protocols were utilized to process and summarize the data, providing key insights into the system's impact.

Research Locale and System Validators

The study was conducted in seven senior high schools within the Tacurong City Division, each with unique programs and student populations. For example, School A serves 5,000 students with academic and vocational tracks, while smaller schools like School F and School G focus primarily on specific academic strands. The system was validated by stakeholders, including guidance counselors, advocates, and administrators, who provided feedback using the TAM2 framework. Their insights were critical in evaluating the technology's perceived usefulness, ease of use, and capacity to address the challenges of strand selection.

Data Gathering and Statistical Analysis

Data collection spanned five years (2018–2024), focusing on students' demographics and average grades, ensuring anonymity in line with FERPA and the Data Privacy Act. Records with a minimum grade average of 85 percent were selected, creating a dataset of 1,112 instances encoded in .xls and converted to ARFF format for WEKA processing. SMOTE and resampling were used to balance the dataset and optimize model accuracy. The TAM2 surveys, administered after system demonstrations, captured user acceptance and feedback. Statistical tools, including mean and standard deviation, provided central and variability measures, while accuracy metrics assessed the predictive performance of the strand recommendation model.

RESULTS

Table 1
Classifier Accuracy Rate

Classifier	Classification Accuracy Rate
Random Forest	95.25%
Deep Neural Networks	84.70%
Naïve Bayes	52.99%

Table 1 presents the classification accuracy rates for three machine learning classifiers: Random Forest, Deep Neural Networks, and Naïve Bayes.

Each classifier's performance is evaluated based on its accuracy rate, which reflects how well the model predicts the correct classes. The accuracy rate is measured through the formula:

Random Forest achieves the highest classification accuracy at 95.25 percent, aligning with the recent findings by Smith and Jones (2019), emphasizing its robustness in handling diverse datasets through ensemble learning techniques. This effectiveness stems from combining multiple decision trees to enhance accuracy and minimize overfitting, as Zhang et al. (2020) support. Deep neural networks (DNN) follow with an accuracy rate of 84.70 percent, highlighting their suitability for processing large and complex datasets. Recent research by Chen and Wang (2020) confirms that while DNNs perform well on intricate patterns, they require extensive computational resources and careful tuning. Meanwhile, Naïve Bayes reports the lowest accuracy at 52.99 percent, consistent with the findings of Lee and Park (2021), who noted its limitations in managing datasets with noise or complex interdependencies due to its feature independence assumption. Overall, Random Forest surpasses both DNN and Naïve Bayes, delivering superior performance through ensemble methods, while DNN excels with large datasets, and Naïve Bayes remains less effective in complex scenarios.

This process was performed in WEKA after executing preprocessing procedures such as SMOTE and instance resampling. SMOTE (Synthetic Minority Over-sampling Technique) has been widely adopted in data mining to address class imbalance in datasets, particularly in classification problems. According to Chawla et al. (2019), SMOTE effectively generates synthetic samples for the minority class by interpolating between existing instances, rather than merely duplicating them. This method is particularly valuable in datasets where a disproportionate number of instances exist in the majority class compared to the minority class, as supported by research from Zhao and Wu (2021). By mitigating the imbalance, SMOTE improves the classifier's ability to recognize patterns in the minority class, leading to enhanced performance in predictive modeling tasks.

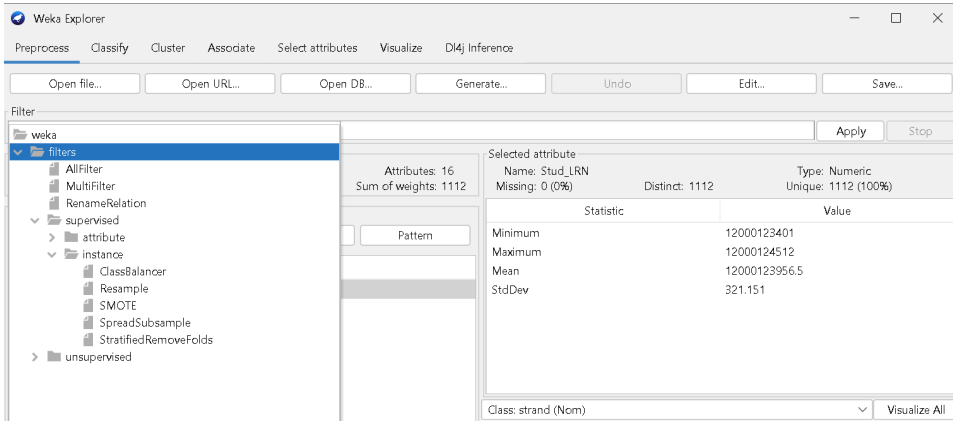


Figure 2. SMOTE on WEKA application

Developed Application

The Iterative Model of the Software Development Life Cycle (SDLC) was utilized to develop the PathFinder application. This approach, as described by Kumar and Singh (2020), emphasizes repeated cycles of development and refinement to ensure continuous improvement and adaptability to user needs. During the planning phase, critical components were identified, including determining suitable applications for system creation, utilizing WEKA for model development, selecting appropriate algorithms for model comparison, defining the types of system users, specifying necessary functionalities, and outlining data collection strategies for model creation. The iterative approach allowed for regular feedback incorporation, enhancing the system's design and functionality according to Patel and Mehta (2021).

Under the analysis phase, data collection was planned based on where and what type of data would be collected, and it was collected from 7 different public schools in the city of Tacurong after appropriate permissions from authorities were in place to secure a smooth collection flow. The attribute inclusion was also analyzed based on the available data from the permanent record called School Form 10.

The design phase focuses on creating a detailed blueprint for the system based on requirements identified during the analysis phase, outlining its architecture, components, and interfaces to guide implementation. This phase

involves defining system components, interactions, and data storage structures, such as databases, tables, and schemas, according to Chen and Zhao (2020). Additionally, it includes creating user interface layouts through mockups or drawings, adhering to design standards like color schemes and navigation, and incorporating security measures to safeguard data Ahmed and Khan (2021). For integrating WEKA, developed in Java, with a PHP-based application using a MySQL backend and XAMPP proxy server, the Command-Line Interface (CLI) is employed. This integration approach, as discussed by Lee and Park (2019), enables PHP to perform machine-learning tasks such as classification, training, and testing by executing commands through functions like `exec()` or `shell_exec()`. The algorithm selection process included evaluating popular classification algorithms, such as deep neural networks, Naïve Bayes, and Random Forest, with Naïve Bayes chosen initially for strand prediction due to its simplicity and availability, consistent with recommendations by Zhao and Wu (2021).

The development of strand prediction models utilized the encoded dataset and algorithms such as Naïve Bayes, Deep Neural Networks, and Random Forest, with preprocessing carried out using WEKA facilities like SMOTE and resampling. SMOTE was applied to address the class imbalance, as Zhao and Wu (2021) recommended, while resampling techniques ensured uniformity and reduced bias in the dataset (Lee & Park, 2019). Additionally, the dataset underwent data manipulation to correct miscoded values, such as converting numeric data to characters where necessary, a critical step to ensure data consistency Ahmed and Khan (2021). Before model creation, the dataset was converted to the .arff file format, input for WEKA-based machine learning tasks (Chen & Zhao, 2020). The deliverables included models and functional prototypes with basic prediction capabilities, enabling an initial evaluation of their performance and utility in strand prediction.

During the application development phase, a functional prototype was created based on the selected Naïve Bayes algorithm and the system design. The prototype features two types of users: the administrator and the general user. The user interfaces for both roles are illustrated in Figures 4 and 5, respectively.

The administrator's interface is distinguished by an orange background, providing a clear visual cue that it is intended for administrative use, as depicted in Figure 4. The administrator can create user accounts, assign models and data formats, and upload and delete models in the system's database through this

interface, depicted in Figure 6.

In contrast, the general user's interface is characterized by a blue background designed to perform a more limited set of tasks, as shown in Figure 5. The user can upload pre-formatted and encoded student data, trigger the analysis process by clicking an "Analyze" button, and print the resulting output depicted in Figure 7. Although WEKA typically requires data in the .arff format, the system automatically converts the uploaded .xls file into the required .arff format, ensuring smooth integration with the WEKA machine-learning model.

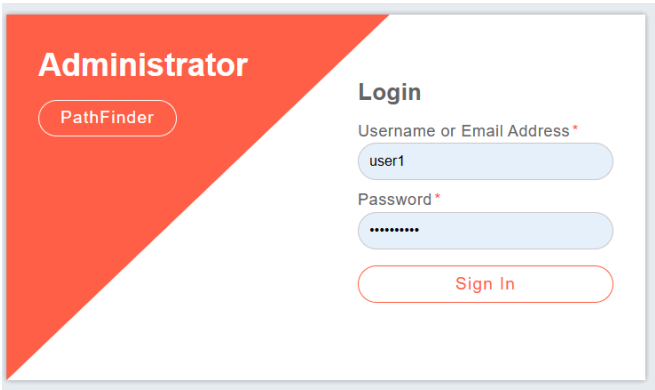


Figure 4. Administrator's Interface

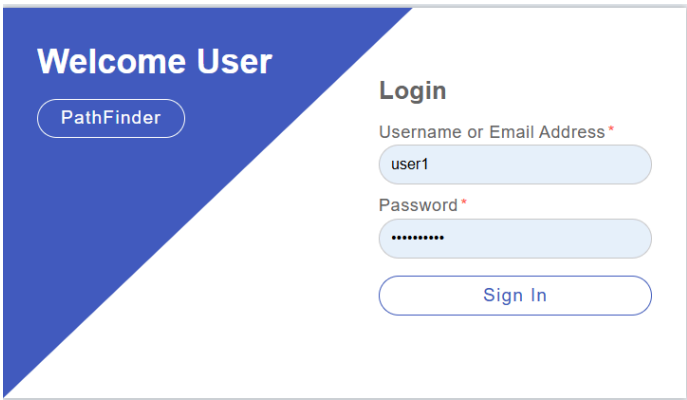


Figure 5. User's Interface

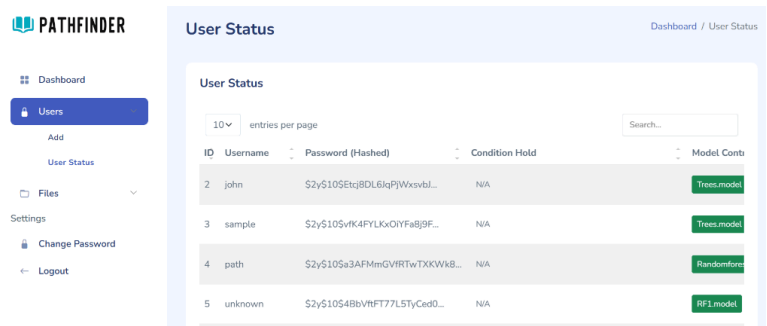


Figure 6. Administrators Task View

The testing phase of the development is conducted by conducting basic testing to verify the functionality and accuracy of the prototype. Loading first is the more straightforward type of algorithm with fewer instances. The data is first fed to WEKA, preprocessed, and tested in the WEKA application to produce predictions. WEKA produced and tested the model, and the same sample data was loaded into the system to test and compare results. Once the results are the same, the system can test another set of models and algorithms and another dataset following the same set of procedures. This iterative approach allows flexibility and continuous improvement throughout development, ensuring that the final strand prediction application meets the desired requirements and achieves optimal performance.

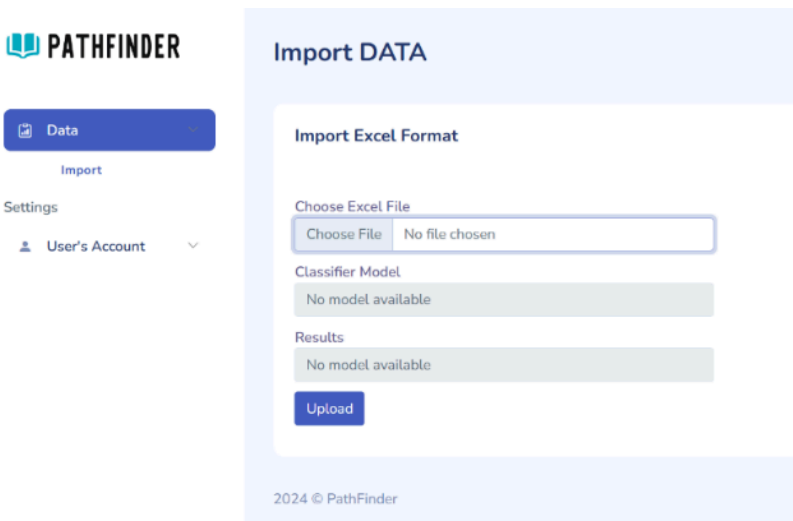


Figure 7. User’s Task

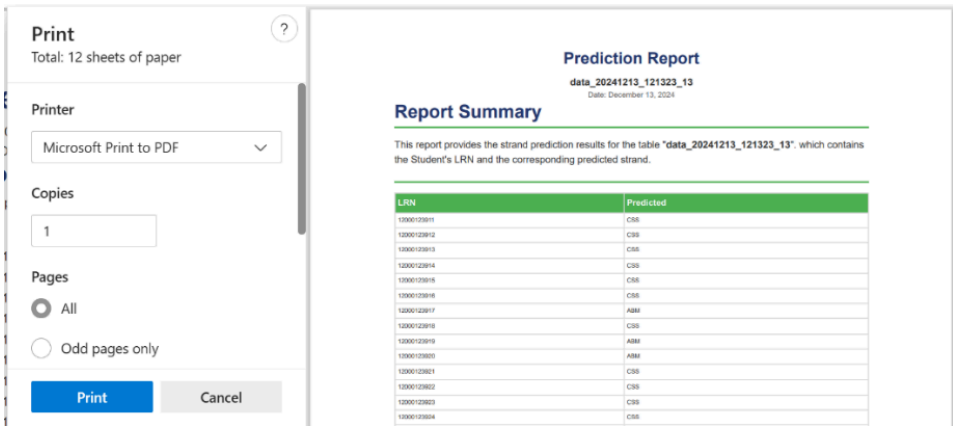


Figure 8. User's Print Output

The printed outputs or results containing the LRN (Learners Reference Number) and the predicted strands, as depicted in Figure 8, were distributed to the students individually through scheduled sessions before they graduated from Grade 10 and transitioned to Grade 11. Guidance counselors and advocates administered the distribution. This approach provided the students with additional information and helped them understand how to choose their strands in Senior High School.

Applications' Level of Acceptance

Table 4
Level of acceptance of the developed application

Perceived Usefulness	Mean	SD	Description
1. Guiding students well using the SPS.	4.62	0.53	Strongly Agree
2. Giving constructive advice on the possible strand of the students using an SPS.	4.60	0.6	Strongly Agree
3. Students knowing the possible strand they will enroll in later.	4.76	0.48	Strongly Agree

4. The SPS is useful in their job.	4.77	0.48	Strongly Agree
Category Mean	4.68	0.52	Strongly Agree

Perceived ease of use	Mean	SD	Description
1. Easily encoding the data in the SPS.	4.64	0.52	Strongly Agree
2. The user interface of the SPS is easy to understand.	4.48	0.63	Strongly Agree
3. Easily editing the data using the SPS.	4.59	0.54	Strongly Agree
4. Finding it easy to trouble shoot the SPS if error occurs.	4.21	0.63	Strongly Agree
Category Mean	4.46	0.58	Strongly Agree

Intention to use	Mean	SD	Description
1. Intending to use the SPS when they advise students about the strand they will select later.	4.59	0.63	Strongly Agree
2. Intending to use the SPS instead of the traditional procedure when I advise students about the strand they will select later.	4.64	0.52	Strongly Agree
Category Mean	4.61	0.58	Strongly Agree
Subjective Norm	Mean	SD	Description
1. The Principal believes that they should use the SPS.	4.62	0.59	Strongly Agree
2. Their colleagues find the SPS useful.	4.64	0.56	Strongly Agree
Category Mean	4.63	0.58	Strongly Agree

Voluntariness	Mean	SD	Description
1. Voluntarily using the SPS.	4.68	0.58	Strongly Agree
2. Their supervisor does not require them to use the SPS.	3.98	1.16	Agree
3. Although it might be helpful, using the SPS is certainly not compulsory in their job.	4.28	1.01	Strongly Agree
Category Mean	4.31	0.92	Strongly Agree

Image	Mean	SD	Description
1. Their colleagues find their office more effective using the SPS.	4.49	0.67	Strongly Agree
2. The students find their advice more believable using the SPS.	4.53	0.64	Strongly Agree
Category Mean	4.51	0.65	Strongly Agree
Job Relevance	Mean	SD	Description
1. In their job, the usage of the SPS is important.	4.70	0.61	Strongly Agree
2. In their job, the usage of the strand prediction system is relevant.	4.66	0.59	Strongly Agree
Category Mean	4.68	0.60	Strongly Agree
Output Quality	Mean	SD	Description
1. The quality of the output from the SPS is high.	4.47	0.64	Strongly Agree
2. They have no problem with the quality of the SPS's output.	4.43	0.72	Strongly Agree
Category Mean	4.45	0.68	Strongly Agree
Result Demonstrability	Mean	SD	Description
1. They have no difficulty telling others the results of the SPS.	4.45	0.61	Strongly Agree
2. They could communicate to others the consequences of using the SPS.	4.43	0.61	Strongly Agree
3. The results of the SPS are apparent to them.	4.40	0.63	Strongly Agree
4. They would have difficulty explaining why using the SPS may or may not be beneficial.	3.87	1.06	Agree
Category Mean	4.29	0.73	Strongly Agree
Overall mean	4.56	0.65	Strongly Agree

The data in Table 4 presents the Strand Prediction System (SPS) acceptance levels based on various constructs aligned with the Technology Acceptance Model 2 (TAM2). The overall mean score is 4.56, indicating respondents "strongly agree" on the system's effectiveness and utility, while the standard deviation of 0.65 reflects moderate consistency among responses (Chen & Zhao, 2020).

The Perceived Usefulness (PU) achieved a high mean score of 4.68, with low variability ($SD = 0.52$), emphasizing its significant role in guiding students and facilitating strand selection. Similarly, Perceived Ease of Use (PEOU) garnered a mean of 4.46, indicating users generally found the system intuitive, though troubleshooting errors showed slightly less agreement (mean = 4.21). These findings align with recent research by Ahmed and Khan (2021), who demonstrated that systems rated high in PU and PEOU tend to show higher acceptance. The Intention to Use (IU) construct scored a mean of 4.61, underscoring strong support for replacing traditional methods with SPS due to its practical relevance, as also noted in studies by Zhao and Wu (2021). Additionally, the influence of social factors, as reflected in the Subjective Norm (SN) with a mean of 4.63, highlights the role of support from principals and colleagues in encouraging system adoption, consistent with findings by Lee and Park (2019).

Constructs such as Image, Job Relevance, and Output Quality also demonstrated strong acceptance, with means exceeding 4.45, emphasizing the SPS's professional significance and output reliability (Patel & Mehta, 2021). Voluntariness, with a mean of 4.31, shows moderate agreement on users adopting the SPS without coercion, though with higher variability ($SD = 0.92$). Meanwhile, Result Demonstrability, with a slightly lower mean of 4.29, reveals challenges in effectively communicating the SPS's outcomes, indicating opportunities for enhancement in result presentation.

Studies validate the strong relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Intention to Use (IU) in technology adoption. Venkatesh and Davis (2000) established these relationships, aligning with the current table's findings, where systems perceived as useful and user-friendly gain higher acceptance. Teo (2019) highlighted that pre-service teachers emphasized job relevance and PU as key adoption factors, consistent with the table's results. Similarly, Liu et al. (2020) found a high mean for PU

(4.6) and IU (4.5) in e-learning systems, underlining the significance of perceived utility on behavioral intentions. However, Park et al. (2020) revealed contrasting results in mobile learning, where variability in PU and IU responses highlighted the impact of demographic factors, such as technological familiarity and perceived complexity, on adoption consistency.

The overall findings of this table reflect strong acceptance of the SPS, with particularly high ratings for its perceived usefulness, ease of use, and job relevance. However, areas like result demonstrability and voluntary usage show opportunities for refinement. These results are supported by studies emphasizing the predictive power of PU and PEOU for intention to use technology. However, contrasting research highlights the importance of user-specific factors in shaping acceptance levels.

CONCLUSION

Implementation Plan

This implementation plan outlines a systematic approach to deploying a technological application across a school division, ensuring readiness, infrastructure adequacy, training, and evaluation. The process begins with gaining approval from division offices by submitting formal letters, a crucial step to ensure administrative alignment and support. Next, infrastructure assessment evaluates the availability of IT resources across schools, followed by the acquisition or assignment of PCs in each school, which is critical for system operations. Additionally, the necessary software is installed in these devices, ensuring full functionality.

Data preparation follows, where schools provide and format the required data for the system, setting the stage for pilot testing. Feedback gathered during this phase addresses potential issues, aligning with guidelines from Lee and Park (2019). Extensive training sessions are conducted to familiarize users with system functionalities and emphasize data security and privacy, equipping them to handle information responsibly and ensuring compliance with regulatory standards. Lastly, a robust monitoring and evaluation process is designed to track the application's usage and overall impact, using metrics and regular reporting to identify areas for optimization. This step-by-step strategy aims to achieve seamless deployment, with budget allocations sourced from MOOE at every stage.

The study's key findings emphasize patterns, trends, and insights derived

from the data. The Random Forest algorithm emerged as the best-performing model, achieving a classification accuracy of 95.25 percent, outperforming Deep Neural Networks (84.70%) and Naïve Bayes (52.99%). Its ensemble learning approach proved effective in minimizing overfitting and handling diverse datasets. Data preprocessing techniques like SMOTE were vital in addressing class imbalances and refining the dataset for classification in WEKA.

The development of the PathFinder application followed the Iterative Model of the Software Development Life Cycle (SDLC), starting with data collection from seven public schools in Tacurong City. The system integrated WEKA with a PHP-based application, initially employing Naïve Bayes for strand prediction but evolving into a functional prototype capable of managing and analyzing student data. Designed with user-friendly interfaces for administrators and general users, the prototype underwent extensive testing to meet functional and accuracy goals. This iterative development process provided a robust framework for enhancing the system's effectiveness, ensuring alignment with strand prediction objectives.

The implementation plan for deploying the SPS across Tacurong's Schools Division emphasized readiness and sustainability, incorporating infrastructure preparation, pilot testing, and training. Focusing on data security, continuous monitoring, and feedback collection ensures the system's long-term success and adaptability, making it a valuable tool for improving strand selection processes. To promote the global implementation of the Strand Prediction System (SPS), it is vital to emphasize its adaptability to diverse educational contexts through a modular design powered by machine learning. The system can be tailored to fit specific curricula, demographic considerations, and educational requirements worldwide. Its user-friendly interface, robust data security, and training programs suit various school settings. Collaboration among local education stakeholders, including administrators, counselors, and IT experts, will ensure successful implementation. Compliance with international data privacy standards like GDPR, FERPA, and multilingual support will foster inclusivity (Park et al., 2020). Additionally, a cloud-based infrastructure can address resource disparities, while regular updates and feedback loops ensure scalability, reliability, and relevance to evolving global educational needs.

For successful deployment in the Tacurong City Schools Division, establishing an online platform is critical to provide streamlined access and maintenance for administrators and users. Investing in higher-capacity web

servers will also ensure that all data is efficiently managed on a single cloud server, accommodating the needs of all stakeholders. Comprehensive training sessions should accompany the system and IT support, enabling seamless integration into existing academic workflows. These measures will strengthen the infrastructure required for the SPS to operate effectively, catering to the division's unique educational landscape. Additional attributes like student engagement levels, socioeconomic background, extracurricular activities, standardized test scores, and psychological profiles should be incorporated to enhance the SPS further. These factors offer deeper insights into student potential, leading to more personalized and accurate strand predictions. Real-time input from teachers, guidance counselors, and parents could further refine predictions, ensuring the system aligns with holistic student development. By addressing diverse student profiles and offering tailored recommendations, the SPS can provide impactful guidance to students, helping them achieve academic and career success.

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