International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A Knn - Powered Evaluation System for Students' Performance in Computer Programming 1 and Early Intervention

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Abstract

The evaluation of student performance in Computer Programming 1 at Perpetual Help College of Manila is commonly based on traditional methods such as quizzes, exams, laboratory activities, and coding projects. While these approaches measure academic output, they often fail to identify struggling students early, leading to poor performance and low retention in the subject. Instructors also lack a system that can analyze student data and provide timely insights for intervention.

To address this concern, this study proposes the development of a KNN-Powered Evaluation System that utilizes the K-Nearest Neighbors (KNN) algorithm to analyze student performance data and predict academic outcomes. By using indicators such as quiz scores, attendance, and laboratory performance, the system can identify at-risk students and provide early intervention through data-driven insights and personalized recommendations. This approach aims to enhance teaching strategies and improve student success in Computer Programming 1.

INTRODUCTION

Assessing and predicting student performance has become a crucial element in modern academic institutions, particularly in foundational technical courses such as Computer Programming 1. These subjects demand not only content mastery but also logical reasoning, algorithmic thinking, and continuous practice—skills that many first- year students struggle to develop. As noted in recent studies, programming courses consistently show higher failure and dropout rates compared to other introductory subjects due to cognitive load, abstract concepts, and the complexity of problem- solving tasks (Ahmed, 2024). When early academic difficulties remain undetected, students often fall behind rapidly, making recovery challenging despite instructor intervention. Traditional evaluation methods within many higher education institutions typically rely on summative assessments—periodic exams, static grade reports, and manually computed performance summaries. While these methods fulfill administrative requirements, they provide limited predictive insights and often identify academic risks only after a student's

performance has significantly declined. Such reactive processes hinder timely intervention and reduce the opportunity for targeted instructional support. Instructors frequently lack analytic tools capable of monitoring subtle performance trends, integrating multiple assessment sources, or detecting early signs of academic decline. To address these gaps, this study proposes the development of a K-NN-Powered Evaluation System designed specifically for Monitoring Student Performance in Computer Programming 1 at Perpetual Help College of Manila. The system integrates machine learning, automated grade analysis, and AI-generated recommendations to shift from reactive evaluation to proactive monitoring.Unlike traditional LMS-based grading tools, the system consolidates quizzes, activities, exams, and attendance into a unified dataset from which the K-Nearest Neighbors (K-NN) algorithm predicts the likelihood of student success or academic risk. Based on identified patterns, the system generates recommendations, supplemental learning resources, and early-warning indicators to support both students and instructors. The K-NN algorithm has been widely recognized for its simplicity, interpretability, and strong performance in classification tasks within educational data mining. Through similarity-based comparison with historical datasets, it effectively groups students according to performance behavior and learning outcomes (Wati et al., 2023). This enables early detection of at-risk learners by analyzing multi-dimensional factors such as evaluation scores, attendance patterns, participation metrics, and trend- based grade fluctuations. Machine learning approaches like K-NN support the broader framework of data-driven education, where predictive analytics guide academic interventions and instructional decision-making (Sharma & Kumar, 2021). Recent literature supports the use of machine learning for academic early-warning systems. Iqbal et al. (2022) highlight the capability of supervised models to identify learning deficiencies before they escalate, while Ahmed (2024) emphasizes the value of integrating data mining techniques in educational institutions to enhance retention and performance outcomes. By incorporating these insights, the proposed system demonstrates the importance of blending predictive analytics with day-to-day academic management practices. This study aims to contribute to this growing field by designing a system that not only provides a Learning Management System but also monitors performance trends, visualizes learning progress, predicts academic risks, and provides AI-driven recommendations. Through these features, the system supports instructors in implementing timely interventions while empowering students to improve their learning outcomes using personalized guidance. Ultimately, the development of this K-NN- Powered Evaluation System seeks to enhance academic success, reduce failure rates, and strengthen the quality of programming instruction within the institution.

METHODS

This study utilizes the Descriptive Developmental Research Method to systematically examine the development, functionality, and perceived effectiveness of the K-NN–Powered Student Performance Evaluation System for Computer Programming 1 at Perpetual Help College of Manila. Descriptive research is appropriate because the study aims to observe and document how the system behaves in an authentic academic environment without manipulating variables, allowing researchers to present a factual and data-driven depiction of system implementation (Chen et al., 2025).The researchers began by identifying recurring issues in the traditional evaluation process, such as delayed feedback, the absence of early warning mechanisms for struggling students, and the lack of predictive insights regarding midterm and final outcomes. These limitations were carefully examined using interviews with instructors, surveys with students, and observations of existing LMS workflows. The findings established the contextual need

for a system capable of providing continuous academic tracking and predictive analytics within the course environment (Fazil et al., 2024). Following this, the system's design and operation were documented in detail, focusing on how the K-Nearest Neighbors algorithm processes student academic data. The model analyzes indicators—including prelim grades, midterm grades, quiz scores, attendance, lab performance, and engagement—to classify students as "Likely to Pass" or "Likely to Fail." For students with only prelim data available, the K-NN model predicts expected midterm and final standings based on historical grade patterns of similar students. When both prelim and midterm grades are available, the system predicts the student's final performance and classification with greater accuracy (Musthofa et al., 2024; Fauzi et al., 2025). Additionally, the descriptive method allowed the researchers to evaluate the usability, practicality, and accuracy of the system through user walkthroughs, system testing, and feedback collection. These evaluations provided insight into how automated predictions, LMS integration, and AI-generated recommendations support academic monitoring. The findings highlight how machine learning—specifically the K-NN algorithm—can enhance decision-making, streamline evaluation processes, and improve student outcomes in Computer Programming 1 (Yu & Liu, 2022; Orji & Vassileva, 2022). By applying the descriptive research method, this study presents a clear and comprehensive depiction of how the evaluation system performs within an actual educational setting. More importantly, it demonstrates the significance of early detection and data-driven intervention in improving learning outcomes for students enrolled in technical and skill- driven subjects such as Computer Programming 1 at Perpetual Help College of Manila.

RESULTS AND DISCUSSION

This chapter deals with the gathered data that were analyzed and interpreted for better understanding of the study. The framework of the analysis and interpretation was guided by the problems stated in chapter 1.

Table 1 presents the IT experts' evaluation of the system's Functionality,focusing on accuracy, correctness of operations, and compliance with the intended academic requirements under ISO/IEC 25010. The first indicator, which measures whether the system correctly implements grading criteria and computation formulas, obtained a weighted mean of 3.00, interpreted as Functional. The system's K-NN algorithm also received a weighted mean of 4.00, which falls under Highly Functional, indicating strong expert confidence in its capability to generate personalized recommendations and supplemental resources. Meanwhile, the effectiveness of integrated tools and modules in supporting academic workflows earned a weighted mean of 3.00, also interpreted as Functional. Overall, the category achieved an average weighted mean of 3.33, interpreted as Functional, demonstrating that the system meets essential functional requirements and performs intended tasks with accuracy and reliability.

Table 1: Level of Effectiveness in Terms of Functionality (IT Experts)

Descriptions	Weighted Mean	Interpretation
The system ensures that all grading criteria and computation formulas are correctly implemented in accordance with the course requirements.	**3.00**	**FUNCTIONAL**
The system's K-NN algorithm accurately generates		

personalized lesson recommendations and supplementary learning resources based on each student's performance data and identified weaknesses.	**4.00**	**HIGHLY FUNCTIONAL**
The system's integrated tools and modules efficiently assist teachers in managing assessments and tracking student progress, while enabling students to monitor their performance and improvement areas.	**3.00**	**FUNCTIONAL**
AVERAGE WEIGHTED MEAN	**3.33**	**FUNCTIONAL**

Table 2 shows the IT experts' assessment of the system's Usability, focusing on ease of use, user navigation, clarity of system feedback, and adherence to user-centered design key attributes under ISO/IEC 25010. The intuitiveness of the interface for teachers, students, and administrators received a weighted mean of 3.67, interpreted as Highly Usable. The ability of users to perform tasks without additional training earned a weighted mean of 3.33, interpreted as Usable. System feedback messages and AI- generated recommendations were rated with a weighted mean of 3.00, also interpreted as Usable. The system's adherence to user-centered design principles received a weighted mean of 3.33, rated as Usable. Collectively, these results produced an average weighted mean of 3.33, indicating that the system is Usable and accessible to all user groups with minimal learning barriers.

Table 2: Level of Effectiveness in Terms of Usability (IT Experts)

Descriptions	**Weighted Mean**	**Interpretation**
The user interface for teachers, students, and administrators is intuitive and easy to navigate.	**3.67**	**HIGHLY USABLE**
Users can perform tasks (e.g., creating activities, taking quizzes, viewing grades) without additional training.	**3.33**	**USABLE**
System feedback messages and AI recommendations are clear and understandable.	**3.00**	**USABLE**
The system's design adheres to user- centered design principles.	**3.33**	**USABLE**
AVERAGE WEIGHTED MEAN	**3.33**	**USABLE**

Table 3 presents the evaluation of Reliability, which assesses the system's stability, consistency, error resistance, and ability to maintain data integrity. The system's continuous operation without crashes obtained a weighted mean of 2.67, interpreted as Reliable. The retention of grades and submissions after server interruptions received a weighted mean of 3.33, also interpreted as Reliable. The K-NN algorithm's ability to generate consistent recommendations across grading periods earned a weighted mean of 3.33, likewise interpreted as Reliable. Additionally, system responsiveness under heavy user load obtained a weighted mean of 3.33, interpreted as Reliable. Overall, the category achieved an

average weighted mean of 3.17, interpreted as Reliable, indicating that the system performs reliably and maintains stability across varying operational conditions.

Table 3. Level of Effectiveness in Terms of Reliability (IT Experts)

Descriptions	Weighted Mean	Interpretation
The system operates continuously without unexpected crashes or errors.	**2.67**	**RELIABLE**
Student grades and submissions are correctly saved and retained after server interruptions.	**3.33**	**RELIABLE**
The KNN algorithm produces consistent and reliable recommendations across grading periods.	**3.33**	**RELIABLE**
The platform remains accessible and responsive even under heavy user load.	**3.33**	**RELIABLE**
AVERAGE WEIGHTED MEAN	**3.17**	**RELIABLE**

Table 4 summarizes the evaluation of Efficiency, which examines system processing speed, responsiveness, and resource optimization under ISO/IEC 25010. Loading time for quiz results, grades, and dashboards received a weighted mean of 2.67, interpreted as Efficient. The system's capability to handle multiple simultaneous users without lag earned a weighted mean of 4.33, interpreted as Very Efficient, the highest score in the category. Memory and processing resource optimization received a weighted mean of 3.33, interpreted as Efficient, while system responsiveness during large dataset processing including multiple student records and K-NN computations also received 3.33, and interpreted as Efficient. These results produced an average weighted mean of 3.17, confirming that the system is Efficient and performs smoothly even under high processing demands.

Table 4. Level of Effectiveness in Terms of Efficiency (IT Experts)

Descriptions	Weighted Mean	Interpretation
The system loads quiz results, grades, and dashboards within an acceptable time frame.	**2.67**	**EFFICIENT**
The system can handle multiple simultaneous users without noticeable lag or slowdown.	**4.33**	**VERY EFFICIENT**
The system optimizes memory and processing resources to maintain smooth performance during peak usage.	**3.33**	**EFFICIENT**
The system sustains optimal performance and responsiveness even when processing extensive datasets, including multiple student records, and K-NN evaluation computations.	**3.33**	**EFFICIENT**

AVERAGE WEIGHTED MEAN	**3.17**	**EFFICIENT**

Table 5 illustrates the experts' evaluation of Compatibility, which assesses the system's cross-platform performance, interoperability, and ability to operate alongside external applications core dimensions of ISO/IEC 25010. The system's functionality across major web browsers received a weighted mean of 4.00, interpreted as Highly Compatible. Its capability to integrate and exchange data with other Learning Management Systems earned a weighted mean of 3.00, interpreted as Compatible. The system's stable performance when used with other applications running simultaneously received a weighted mean of 3.00, also interpreted as Compatible. Additionally, its support for standardized data formats Excel, CSV, PDF, JSON, and XML was rated with a weighted mean of 3.67, interpreted as Highly Compatible. These results produced an average weighted mean of 3.42, confirming that the system is Compatible and adaptable across diverse digital platforms and environments.

Table 5. Level of Effectiveness in Terms of Compatibility (IT Experts)

Descriptions	Weighted Mean	Interpretation
The system works properly across major web browsers (e.g., Chrome, Edge, Firefox).	**4.00**	**HIGHLY COMPATIBLE**
The system is capable of integrating and exchanging student performance data with other Learning Management Systems (LMS) through compatible data structures and standardized exchange formats.	**3.00**	**COMPATIBLE**
The system operates efficiently even when other applications are running simultaneously on the same device.	**3.00**	**COMPATIBLE**
The system supports standard data formats (e.g., Excel, CSV, PDF, JSON, and XML) for exporting and sharing information with other platforms.	**3.67**	**HIGHLY COMPATIBLE**
AVERAGE WEIGHTED MEAN	**3.42**	**COMPATIBLE**

Table 6 presents the educators' evaluation of the system's Functional Suitability based on ISO/IEC 25010 standards. Results show that teachers find the system functionally capable in supporting classroom evaluation tasks. They rated the system as Functional 3.20 for efficiency in monitoring student performance and Highly Functional 3.40 for providing valuable insights through K-NN computations. The AI- generated recommendations were also rated Highly Functional 3.35, indicating usefulness in identifying at-risk students. Additionally, teachers perceived the system as Highly Functional 3.45 in reducing the time spent computing grades and Highly Functional 3.50 in enhancing classroom management and academic decision-making. With an overall weighted mean of 3.38, interpreted as Highly Functional, the results confirm that the system effectively fulfills its intended purpose and

supports data- driven instructional processes.

Table 6. Level of User Acceptance in Terms of Functional Suitability (Teachers)

Descriptions	Weighted Mean	Interpretation
The system helps me monitor student performance in Computer Programming 1 more efficiently than manual evaluation.	**3.20**	**FUNCTIONAL**
The system's K-NN-powered evaluation provides valuable insights into students' learning patterns and academic progress.	**3.40**	**HIGHLY FUNCTIONAL**
The AI-generated recommendations assist in creating targeted interventions for at-risk students.	**3.35**	**HIGHLY FUNCTIONAL**
The system reduces time spent on computing and recording grades.	**3.45**	**HIGHLY FUNCTIONAL**
The system enhances overall classroom management and academic decision- making.	**3.50**	**HIGHLY FUNCTIONAL**
AVERAGE WEIGHTED MEAN	**3.38**	**HIGHLY FUNCTIONAL**

Table 7 illustrates the teachers' assessment of the system's Interaction Capability, reflecting its usability under ISO/IEC 25010. Teachers rated the interface as Highly Interactive 3.50 for ease of navigation, while activities such as creating grades, quizzes, and attendance were rated Highly Interactive 3.65, demonstrating strong ease of use. The clarity and interpretability of AI recommendations also received Highly Interactive 3.65 ratings. Guidance features and instructions during tasks were evaluated as Highly Interactive 3.10, and the system's help messages for errors were rated Highly Interactive 3.20. Overall, the system achieved an average weighted mean of 3.42, interpreted as Highly Interactive, confirming that it delivers an intuitive, user-friendly experience even for teachers with limited technical background.

Table 7. Level of User Acceptance in Terms of Interaction Capability (Teachers)

Descriptions	Weighted Mean	Interpretation
The system interface is easy to navigate and understand without extensive training	**3.50**	**HIGHLY INTERACTIVE**
Creating grades, quizzes, and attendance is straightforward and efficient.	**3.65**	**HIGHLY INTERACTIVE**

The recommendations given by the AI are clearly presented and easy to interpret.	**3.65**	**HIGHLY INTERACTIVE**
The system clearly indicates available features and provides helpful guidance and instructions when performing tasks.	**3.10**	**HIGHLY INTERACTIVE**
The system provides help messages or guidance when encountering errors or unclear tasks.	**3.20**	**HIGHLY INTERACTIVE**
AVERAGE WEIGHTED MEAN	**3.42**	**HIGHLY INTERACTIVE**

Table 8 summarizes teachers' evaluation of the system's Reliability and Quality in Use. The accuracy of K-NN results received a rating of Highly Reliable 3.55, while the system's dependability in tracking student progress was rated Highly Reliable 3.60. The AI recommendation system was evaluated as Highly Reliable 3.65, demonstrating strong trust in its output. Teachers also rated the system's overall functionality and stability as Highly Reliable 3.60, and they affirmed that it meets their expectations as a monitoring tool with another Highly Reliable 3.60 rating. With an average weighted mean of 3.60, interpreted as Highly Reliable, the results confirm that the system consistently performs as expected and provides a stable, accurate environment for academic evaluation.

Table 8. Level of User Acceptance in Terms of Reliability/Quality in Use (Teachers)

Descriptions	**eighted Mean**	**Interpretation**
I am satisfied with the performance and accuracy of the K-NN evaluation results.	**3.55**	**HIGHLY RELIABLE**
The system provides a reliable platform for tracking student progress.	**3.60**	**HIGHLY RELIABLE**
The AI recommendation system provides useful insights for improving student performance.	**3.65**	**HIGHLY RELIABLE**
I am satisfied with the overall functionality and reliability of the system.	**3.60**	**HIGHLY RELIABLE**
The system meets my expectations as an educational performance monitoring tool.	**3.60**	**HIGHLY RELIABLE**
AVERAGE WEIGHTED MEAN	**3.60**	**HIGHLY RELIABLE**

Table 9 presents teachers' evaluation of the system's Flexibility, covering adaptability to classroom workflows, readiness for institutional integration, and potential to replace traditional evaluation procedures. Teachers rated their willingness to adopt the system as High Flexibility 3.30, openness to AI recommendations 3.55, confidence in reducing manual workload and grading errors 3.40, and integration of dashboards and predictive analytics
3.60. Recommending the system for institutional adoption received 3.10. The overall weighted mean of 3.39, interpreted as High Flexibility, indicates that teachers view the system as adaptable.

Table 9. Level of User Acceptance in Terms of Flexibility (Teachers)

Descriptions	eighted Mean	Interpretation
I am willing to adopt the K-NN-Powered Evaluation System as a supplementary tool for monitoring and evaluating student performance in Computer Programming 1.	**3.30**	**HIGH FLEXIBILITY**
I am open to use the system's AI-generated recommendations to guide academic interventions and support struggling students.	**3.55**	**HIGH FLEXIBILITY**
I am confident that the system's automated grade computation and analytics can reduce manual workload and grading errors.	**3.40**	**HIGH FLEXIBILITY**
I am willing to integrate the system's performance dashboards and predictive analytics into my teaching process to enhance data-driven decision-making.	**3.60**	**HIGH FLEXIBILITY**
I would recommend institutional adoption of the system to improve academic performance tracking and early identification of at-risk students.	**3.10**	**HIGH FLEXIBILITY**
AVERAGE WEIGHTED MEAN	**3.39**	**HIGH FLEXIBILITY**

CONCLUSIONS AND RECOMMENDATIONS

The study examined the student performance evaluation methods in Computer Programming 1 at Perpetual Help College of Manila (PHCM) and found that the institution employs a structured process combining lecture and laboratory assessments. Lecture evaluations include class standing, quizzes, assignments, and major exams, while laboratory assessments emphasize hands-on tasks and practical examinations. Faculty members utilize digital platforms such as CodeChum and the PHCM LMS to record grades, automate scoring, and provide timely feedback, though challenges such as large class sizes and rubric-based workloads persist. Key academic factors influencing student success were identified, with periodic grades (Prelim, Midterm, and Final) serving as the strongest predictors of outcomes. Continuous assessments, attendance, and participation also emerged as critical indicators, highlighting the importance of consistent engagement and submission of tasks. The proposed KNN–Powered Student Performance Evaluation System was designed with a relational database schema encompassing user management, academic content, grading, monitoring, and AI-driven prediction modules. This structure supports automated grade computation, real-time tracking, and accurate evaluation. Its intelligent features—including a KNN-based prediction engine, AI recommendation system, automated grade computation, lesson and activity management, attendance tracking, and dynamic dashboards—proved effective in identifying at-risk students and supporting targeted interventions. Evaluation by IT experts using ISO/IEC 25010 standards confirmed the system's high effectiveness across functionality, usability, reliability, efficiency, and compatibility. Similarly, educators rated the system highly in terms of functional suitability, interaction capability, reliability in use, and flexibility, affirming its practicality and readiness for institutional adoption. The study concludes that PHCM's current evaluation practices are structured and consistent, supported by digital platforms, but limited by large class sizes, varying student preparedness, and heavy faculty workload.

Periodic grades, continuous assessments, and attendance are the most reliable predictors of student success, making them essential inputs for early intervention. The proposed KNN-powered system, with its comprehensive database schema and intelligent features, effectively enhances grade management, performance monitoring, and predictive accuracy. IT experts confirmed its compliance with ISO/IEC 25010 standards, validating its technical robustness, reliability, and readiness for academic deployment. Likewise, teachers expressed strong acceptance, recognizing its usefulness in improving grading accuracy, reducing manual tasks, and supporting data-driven instruction. Overall, the system is technically sound, user-friendly, and well-positioned for institutional adoption to strengthen evaluation efficiency and student support at PHCM. To strengthen the KNN–Powered Student Performance Evaluation System, the study recommends continuous dataset expansion and cleansing to improve prediction accuracy, incorporating finer-grained academic indicators such as laboratory performance patterns and activity logs, and optimizing the database for scalability through techniques like indexing, caching, and potential cloud deployment. Enhancements to the AI recommendation engine should focus on adaptive learning pathways and personalized feedback, while a continuous quality assurance framework is advised to maintain compliance with ISO/IEC 25010 standards through regular audits and updates. Finally, ongoing teacher training, support sessions, and customization options for dashboards and reports are encouraged to maximize usability, foster confidence, and ensure smooth institutional adoption. Collectively, these measures will sustain the system's effectiveness, improve early interventions, and support long-term integration into PHCM's academic processes.

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