**Optimizing NAT Readiness: A K-NN Algorithm-Driven AI System and Resource Recommendation for Grade 12 Students at STCFI**

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**INTRODUCTION**

#### Background of the Study

The use of artificial intelligence (AI) and machine learning (ML) in education has become a global focus, with studies centered on personalized learning systems that respond to student requirements. It has been demonstrated that AI- based platforms can dramatically improve learning outcomes by detecting individual weaknesses and adapting study materials accordingly (Rathod & Deshpande, 2023; Shah et al., 2022). Schools globally have adopted machine learning models to monitor student performance, streamline curriculum design, and enhance academic success. The success of these systems is, however, contingent upon the presence of well-structured learning tools and proper learning model selection that supports diverse learning requirements (Kim et al., 2022).

In Southeast Asia, standardized testing is used to inform education policy and assess students' competence. Singapore, Malaysia, and Indonesia have already adopted AI- based learning systems in order to better prepare students for national tests (Huang et al., 2023). These systems are able to offer adaptive learning in the form of customized content suggestions and live monitoring of students' progress. Yet, despite advancements, challenges remain in the form of digital literacy gaps, limited access to internet resources, and educational disparities, especially in the developing world (UNESCO, 2022). Overcoming these obstacles is necessary to provide all students with the benefits of AI-fueled educational developments.

In the Philippines, the National Achievement Test (NAT) is the main component for testing a grade 12 student’s English language proficiency, standardized testing of basic competencies (NME), in mathematics and science and standardized testing of spoken language proficiency (Department of Education, 2024). The National Achievement Test results also serve as indicators of a student’s maturity for higher education and future career opportunities (Garcia & Santos, 2023). Online educational tools exist, but most are not specifically designed to align with the expectations of the National Achievement Test nor do they provide personalized study guidance (Garcia & Santos, 2023).

Despite the increasing use of AI in education, limited research has explored its application in NAT preparation. Existing studies have primarily focused on predicting student performance rather than actively improving test outcomes through AI-driven interventions (Martinez et al., 2023). Additionally, factors such as socioeconomic status, internet accessibility, and school resources remain under examined, restricting the development of inclusive and equitable AI-powered learning solutions (Zheng & Zhang, 2023).

To address these requirements, this study seeks to develop an AI-supported online review system that continuously monitors and evaluates student performance through real-time assessments. Instead of relying on a traditional pre-test and post-test model, the system uses a dynamic, iterative approach that classifies students’ readiness based on ongoing quiz results, topic mastery, and engagement levels. Through this adaptive mechanism, the system identifies knowledge gaps, delivers targeted review interventions, and updates recommendations as students progress. With its machine learning capabilities, particularly the K-Nearest Neighbors (KNN) algorithm, the system ensures personalized content delivery aimed at helping students reach an optimal level of readiness for the National Achievement Test (NAT).

The present study can cover learning gaps and provide equal opportunities for learning by Filipino learners, particularly marginalized ones. Through personalized learning with the support of AI, the present study can make learners' review processes more effective, enhance their NAT scores, and overall readiness for learning. The system can serve as a model of data-driven education programs that can inform policymakers and teachers on how to make learners' learning processes better. In the long run, the present study can serve as an add-on to the entire goal of optimizing country-level performance in education and empowering learners with skills needed in their scholarship and working life.

#### Statement of the Problem

Increased complexity in academic requirements for Grade 12 students necessitates a review system based on machine learning that provides students with personalized learning materials based on their own weaknesses and strengths. Traditional testing systems cannot take into consideration learning rates and hence are not effective in preparing students for standardized tests. For instance, a study comparing traditional and modern assessment approaches highlighted that traditional methods might not effectively address diverse student needs, potentially impacting academic performance (Meylani, 2024). The intersection of data analysis and artificial intelligence in an adaptive system provides a real-world solution for improving review sessions and improving student.

This study aims to develop and test an AI-driven system providing individualized review content to Grade 12 students through machine learning algorithms. Specifically, the study seeks to answer the following research questions:

1. What are the common challenges faced by Grade 12 students in terms of:
   1. Access to quality review materials?
   2. Identifying weak subject areas?
   3. Retaining and applying learned concepts effectively?
2. What is the performance of an AI-powered review system in terms of:
   1. Personalized content recommendations?
   2. Adaptive difficulty levels based on student performance?
   3. Data-driven analytics for tracking progress and improvement?
3. What is the accuracy level of AI-powered review system in terms of
   1. Topic recommendation and student engagement?

* 1. Addressing individual student strengths and weaknesses?

1. What is the level of acceptance of the system in terms of:
   1. Perceived ease of use.

* 1. Perceived usefulness.

#### Significance of the Study

The development of a review system that is adaptive using machine learning for grade 12 students will go a long way in impacting the education and technology sectors. Using artificial intelligence, data analysis, and adaptive learning, this study will aim to maximize the use of review sessions so that students will be offered tailored, data-enriched study plans based on their unique learning needs.

The results of this study will accrue to the advantage of the following stakeholders:

1. **Grade 12 Students**—The AI adaptive reviewing system will give the students an adaptive learning experience wherein they will be able to identify their weak areas, learn from the applicable study material, and score better in college entrance exams and national standardized tests. System suggestions will help in personalizing the studies in a manner that the area of highest priority is targeted, resulting in productive and efficient study sessions.
2. **Teachers and Educators**—Educators will be able to monitor the performance of students based on data-driven insights and analysis provided in the system. Teachers will be able to improve instruction pedagogy and deliver focused academic interventions through the identification of common weak spots. Hand grading relief will also be offered by the platform through automatic analysis of student performance.
3. **Schools and Academic Institutions**—Schools will improve their programs of academic support with the implementation of this review system using AI, and this will result in increased student passing rates in standard tests. The analytics of the system will also improve the curriculum by detecting common knowledge gaps by subject.
4. **Educational Technology Researchers and Developers**—Research will assist in developing AI-based learning systems and examining whether machine learning algorithms can be applied for learning or not. The researchers can feed their recommendations to the research that will be done for the development of adaptive models of learning, recommendation models, and learning software using AI.
5. **Parents and Guardians**—Instant feedback from parents about the process of learning for the child is essential so that parents can observe performance and support at home when and where necessary. The adaptive review system has to be deployed in order to facilitate students maximizing study time productively. 6. Future Applications of AI and Learning—With machine learning, natural language processing, and data analytics embedded in the learning industry, this research will lay the groundwork for future AI-based educational software. The results will unlock the doors to more advanced intelligent tutoring systems, automated feedback systems, and learning prediction analytics.
6. **Future Innovations in AI and Education** – By integrating machine learning, natural language processing, and data analytics into education, this study will serve as a foundation for future AI-powered educational tools. The findings may lead to the development of more advanced intelligent tutoring systems, automated feedback mechanisms, and predictive analytics for academic success.

#### Scope and Limitation of the study

#### Scope

#### This study focuses on the design, implementation, and evaluation of an AI-powered review system to optimize learning experiences for Grade 12 NAT takers. The system applies machine learning-based algorithmic techniques to track learners' performance, identify learning issues, and develop customized study plans.The system is equipped with adaptive learning capabilities that adjust content difficulty levels adaptively according to users' real-time performance to provide an optimized learning path.

#### Important technical highlights of the system are:

#### AI-Based Content Suggestion – Utilizing machine learning to suggest learning material according to individual strength and weakness.

#### Adaptive Difficulty Adjustments – Uses reinforcement learning algorithms to vary question difficulty dynamically based on student performance.

#### Data Analysis & Performance Monitoring – employs data visualization tools for monitoring student usage, accuracy pattern, and overall performance.

#### User-Friendly Web Interface – Created in teacher- and student-friendly UI/UX so that it can be utilized with ease.

#### Limitations

Despite its advanced capabilities, the system has several technical and operational constraints:

1. **Machine Learning Model Constraints** – The accuracy of content recommendations is dependent on the quality and size of the training dataset. The model may require continuous retraining with new educational data to improve accuracy.
2. **Limited Subject Coverage** – The system is optimized for NAT core subjects (Mathematics, Science, English, and Filipino). Other subjects may not be comprehensively supported due to dataset availability.
3. **Internet Dependency** – Since the platform operates as a web-based application, students in areas with poor internet connectivity may experience limited access to system functionalities.
4. **User Adaptation & Learning Curve** – Both students and educators may require initial training to effectively utilize AI-powered features, which could affect adoption rates in the early phases.
5. **External Factors Beyond AI Control** – While the system personalizes learning experiences, external elements such as socioeconomic status, study environment, and student motivation may impact overall learning outcomes, which the AI cannot fully account for.

#### Definition of terms

**AI-Powered Review System:** A web-based platform developed in this study that uses machine learning algorithms, specifically the K-Nearest Neighbors (KNN), to provide personalized content recommendations and adaptive learning experiences to Grade 12 students preparing for the National Achievement Test (NAT). It includes features such as adaptive difficulty, progress tracking, and resource recommendations.

**K-Nearest Neighbors (KNN):** A supervised machine learning algorithm used in this study to classify student readiness levels (Ready, Moderately Ready, Not Ready) based on proximity to previously observed data points in a multidimensional space. The algorithm operates by analyzing similarities in academic data using the Euclidean distance formula.

**National Achievement Test (NAT):** A standardized assessment administered by the Department of Education (DepEd) in the Philippines, evaluating Grade 12 students in core subjects such as Mathematics, Science, English, and Filipino. In this study, NAT readiness is measured and enhanced through AI-powered interventions.

**Personalized Learning:** Refers to the individualized approach adopted by the AI system where students receive content and question sets tailored to their identified strengths and weaknesses based on their performance metrics.

**Adaptive Difficulty:** A dynamic feature of the AI system that adjusts the difficulty level of questions in real time based on the learner’s responses, ensuring that content remains appropriately challenging for knowledge retention.

**Accuracy (in Machine Learning Context):** The percentage of correctly classified student performance outcomes by the KNN model. It measures the proportion of accurate predictions regarding NAT readiness.

**Data Preprocessing:** The method of cleaning, normalizing, and structuring raw academic data to improve the reliability and effectiveness of the KNN algorithm in predicting student performance.

**Algorithm Training:** The process of feeding historical educational data into the KNN algorithm to identify trends and improve prediction accuracy regarding student readiness and learning gaps.

**Student Engagement:** Measured by system usage metrics such as time-on-task, response frequency, and module completion rates. In this study, engagement is used to infer student motivation and system interaction over time.

**Technology Acceptance Model (TAM):** A theoretical model used in this study to measure user acceptance of the AI system, specifically focusing on **Perceived Ease of Use** (how intuitive the system is) and **Perceived Usefulness** (how beneficial the system is to learning).

**Performance Analytics:** Real-time data tracking within the system that captures test scores, topic mastery, and usage patterns. These analytics inform both the students and educators of academic progress and areas needing improvement.

**Artificial Intelligence (AI):** The simulation of human intelligence in machines that are programmed to think, learn, and problem-solve like humans.

**Algorithm:** A process or set of rules to be followed in calculations or other problem- solving operations, especially by a computer.

**Machine Learning:** A branch of artificial intelligence that allows computer systems to automatically learn and improve from experience without being explicitly programmed.

### CHAPTER II

**REVIEW OF RELATED LITERATURE**

This chapter presents a review of relevant literature and studies related to the readiness of Grade 12 students for the National Achievement Test (NAT), the application of the K-Nearest Neighbors (KNN) algorithm in educational data analysis, and the significance of resource recommendations in enhancing student performance. These discussions establish the foundation for the present study and highlight the relevance of data-driven approaches in predicting student preparedness for standardized assessments.

The National Achievement Test (NAT) is a standardized examination administered by the Department of Education (DepEd) in the Philippines to assess student competency in core subjects such as Mathematics, Science, English, and Social Studies (DepEd, 2023). According to Bernardo (2021), NAT performance is influenced by several factors, including instructional quality, student motivation, and access to learning resources. Cruz (2020) emphasized that early preparation and effective teaching methodologies contribute significantly to student readiness, as structured review programs and adaptive learning materials enhance comprehension and retention. Additionally, socio-economic status plays a crucial role in student achievement, as financially disadvantaged students often lack access to supplementary resources needed for effective test preparation (Delos Reyes, 2021). To address this issue, Smith and Brown (2021) suggested that assessment-driven learning strategies, such as data-driven performance tracking and targeted remediation, can significantly improve student outcomes. These findings highlight the necessity of predictive analytics to identify students at risk of low performance and provide timely interventions. Application of the K-Nearest Neighbors(KNN) Algorithm in Education.

The use of machine learning in education has gained significant attention in recent years, particularly in predicting student performance and readiness. The K- Nearest Neighbors (KNN) algorithm, a non-parametric classification method, has been widely applied in educational data analysis due to its effectiveness in identifying patterns and trends (Garcia & Lopez, 2022). Zhang and Wang (2020) demonstrated that KNN could accurately classify students into performance categories by analyzing historical academic data, attendance, and participation levels. Their study found that early identification of at-risk students allowed educators to implement targeted support strategies, improving overall test performance. Similarly, Rahman et al. (2021) explored the benefits of KNN for personalized learning and found that machine learning models helped educators develop customized study plans, resulting in better engagement and comprehension. However, Johnson et al. (2021) noted that the accuracy of KNN predictions depends on the quality and quantity of available data, suggesting that integrating KNN with other machine learning models, such as decision trees or support vector machines, could further enhance prediction accuracy. These studies support the growing demand for data-driven teaching strategies that optimize learning outcomes and improve student preparedness for high-stakes assessments.

The Role of Resource Recommendations in Academic Performance. In addition to predictive analytics, resource recommendations play a critical role in improving student performance. Research has shown that personalized study resources significantly impact learning outcomes by tailoring educational materials to individual student needs (Johnson et al., 2021). Patel and Singh (2020) found that students who utilized AI-driven recommendation systems performed better on standardized tests due to increased motivation and engagement. Digital learning platforms that incorporate machine learning algorithms, such as KNN, can suggest relevant study materials based on a student's strengths and weaknesses, enhancing comprehension and retention. Moreover, Del Rosario and Santos (2022) highlighted the importance of equitable access to learning resources, noting that schools that implemented data-driven resource distribution strategies saw a significant improvement in overall NAT performance.

These findings emphasize the potential of technology-driven education in bridging learning gaps and ensuring that students receive the necessary support to excel in standardized assessments. Research Gaps and Future Directions. Despite the promising findings on student performance prediction, machine learning applications, and resource recommendations, research gaps remain in the context of the Philippine education system. Many existing studies are based on Western education models, which may not fully reflect the challenges faced by Filipino students (Del Rosario & Santos, 2022).

Additionally, the effectiveness of KNN in predicting NAT readiness has not been extensively explored in the local setting. Cruz (2020) noted that most research on student performance prediction in the Philippines relies on traditional statistical methods rather than advanced machine learning approaches. Future studies should focus on integrating KNN with other predictive models to improve accuracy and provide more comprehensive insights into student readiness. Furthermore, while short-term benefits of personalized learning resource recommendations have been established, Kim and Lee (2022) suggested that further research is needed to evaluate their long-term impact on academic success. Addressing these research gaps will contribute to a deeper understanding of how data-driven approaches can enhance student preparedness for standardized tests. Synthesis of Literature.

The review of related literature highlights the importance of assessing student readiness for the NAT, the effectiveness of the KNN algorithm in predicting academic performance, and the role of resource recommendations in improving student outcomes. Existing studies emphasize the need for data-driven strategies to identify at-risk students and provide targeted support. While machine learning applications in education have shown promising results, further research is required to tailor these approaches to the specific challenges faced by Filipino students. By exploring the application of KNN in NAT readiness assessment at Southern Tech College Foundation Inc., this study aims to contribute valuable insights into data-driven student assessment and intervention strategies. The findings of this research may serve as a basis for developing predictive models that enhance academic performance and ensure better test preparedness among students.

While several studies have explored student performance prediction using machine learning algorithms, there are notable gaps in research that this study aims to address. Many existing studies focus on general academic performance prediction rather than readiness for a specific standardized test like the National Achievement Test (NAT). For example, Zhang and Wang (2020) applied the K-Nearest Neighbors (KNN) algorithm to predict student success in general coursework but did not examine its effectiveness in standardized assessments. Similarly, Rahman et al. (2021) demonstrated the use of KNN in predicting at-risk students but did not integrate resource recommendations tailored to test readiness.

Furthermore, most studies on student performance prediction have been conducted in Western or technologically advanced educational systems. Studies by Garcia and Lopez (2022) and Johnson et al. (2021) emphasized the potential of KNN and other machine learning models in predicting academic outcomes, but these studies were conducted in countries with well-established digital learning infrastructures. There is limited research on how KNN can be applied in the Philippine education system, where access to technology, learning resources, and data availability may vary across schools. Additionally, previous studies have focused on machine learning-based prediction models but have not extensively explored the impact of integrating predictive analytics with personalized resource recommendations. Patel and Singh (2020) examined AI-driven learning platforms but did not assess how these recommendations affect students’ actual test performance in high-stakes exams like the NAT. This gap highlights the need for a study that not only predicts student readiness but also suggests targeted learning interventions based on the prediction results. Lastly, while studies such as those by Delos Reyes (2021) and Kim and Lee (2022) discuss factors affecting student performance, they primarily use traditional statistical methods rather than machine learning approaches. These studies lack a data-driven framework that could provide a more dynamic and adaptive analysis of student readiness.

` Korkmaz and Correia (2019) investigated trends in ML research within educational technologies from 2007 to 2017. Analyzing 74 articles, they identified common research areas such as automation, cognitive process assessment, prediction, intelligent tutoring systems, and the opportunities and challenges presented by big data and learning analytics. They recommended expanding geographical diversity in research and incorporating Bayesian and fuzzy logic methods to enrich ML applications in educational technology.

Rivera and Santos (2021) investigated the impact of study habits and resource availability on student performance in national assessments. Their findings indicated that students who engaged in frequent self-assessments, practice tests, and collaborative study groups were better prepared for high-stakes testing. Furthermore, students with access to a wide range of educational resources, including textbooks, online tutorials, and review materials, demonstrated greater confidence and retention of key concepts.

Another study by Villanueva et al. (2022) examined the role of teacher-led review programs in improving student outcomes on standardized tests. Their research found that students who participated in structured classroom review sessions performed significantly better than those who studied independently. The study emphasized the importance of integrating test-taking strategies into the curriculum to enhance student readiness and minimize test anxiety. Similarly, Tanaka (2021) explored the effects of structured test preparation programs on student performance in standardized examinations.The study found that schools with dedicated review and reinforcement programs experienced a 15% increase in their students’ national assessment scores. This underscores the necessity for well- planned test preparation strategies to optimize student learning outcomes.

According to Patel and Kumar (2022), machine learning models, including KNN, have been effective in predicting student success by analyzing previous academic records, attendance, and engagement levels. Their research demonstrated that KNN could accurately classify students into various performance categories, allowing educators to implement early interventions for those at risk of underperforming. Chen and Wu (2021) explored the impact of AI-driven analytics on student performance prediction. Their study revealed that predictive models significantly enhance the accuracy of identifying struggling students. By applying machine learning algorithms to educational datasets, schools can create personalized learning interventions that address specific academic weaknesses. A study conducted by Gonzalez and Martinez (2023) investigated the role of data- driven models in identifying at-risk students before major assessments. The findings highlighted that predictive analytics could help educators design targeted support programs for students who require additional academic assistance. The study also emphasized that integrating AI tools into student assessment practices enables real- time tracking of learning progress. Similarly, Liu et al. (2020) found that AI-assisted learning platforms provide personalized feedback, improving student retention and comprehension. Their research concluded that machine learning could optimize individualized learning paths, ensuring that students focus on areas where they need the most improvement.

According to Kim and Park (2022), predictive analytics enables schools to implement data-driven decision-making in education. Their research found that schools using predictive analytics reported higher student retention rates and improved overall academic achievement. The study emphasized that early identification of struggling students allows educators to design targeted instructional strategies to enhance learning outcomes. Lopez and Garcia (2021) examined the impact of data-driven decision-making on student performance in national assessments. Their findings indicated that predictive models improve curriculum planning; allowing educators to allocate resources effectively based on student performance trends. The study also highlighted that AI-driven analytics could identify knowledge gaps and recommend personalized learning interventions. A study by Navarro (2023) explored the need for localized predictive models in education, particularly in developing countries. The study pointed out that most existing predictive analytics tools are designed based on Western educational settings, making them less applicable in Philippine schools. Navarro suggested that developing localized machine learning models could improve predictive accuracy and better address the specific needs of Filipino students. Furthermore, Thompson and Reed (2021) investigated the effectiveness of AI-based predictive models in forecasting student success in standardized tests. Their study revealed that AI- driven analytics accurately predicted student outcomes and enabled schools to implement data-driven interventions

. The research suggested that integrating predictive analytics into education systems could enhance student preparedness for high-stakes examinations. Lee (2020) proposed integrating predictive analytics with real-time student monitoring systems to enhance learning outcomes. His study found that AI-powered assessment tools helped educators track student progress and adjust instructional methods accordingly. This underscores the importance of using predictive models to support continuous student development.

Emerging studies confirm that AI-powered systems, when designed with adaptive algorithms, offer substantial benefits in addressing diverse student needs. For example, Rivera and Delacruz (2023) demonstrated how adaptive learning environments improved academic performance by offering scaffolded support in subjects where students exhibited weaknesses. Their study emphasized the value of real-time feedback and progress tracking in motivating learners and guiding educators. Likewise, Banzon and Reyes (2022) reported that students using adaptive assessment tools showed a 12% increase in test performance compared to those using static review methods.

The unique context of education in the Philippines, where access to high- quality educational tools remains uneven, underscores the importance of developing localized AI systems. According to Medina et al. (2022), localized algorithms trained on region-specific data improved the predictive accuracy of student performance models by 18% over imported datasets. Their work suggests that AI systems tailored to the Filipino educational environment are more effective in identifying learning gaps and recommending context-appropriate interventions.

The K-Nearest Neighbors (KNN) algorithm remains one of the most accessible and interpretable ML models in educational data mining. Studies by Tiu and Santos (2023) highlight that KNN's simplicity in classifying students based on peer performance makes it ideal for school-level implementation. In their research on senior high school readiness assessments, KNN achieved 82% accuracy in predicting student performance levels when trained on prior academic records and quiz results. The findings underscore the utility of KNN in non-commercial, academic environments where computational efficiency and interpretability are crucial.

There is a growing consensus among scholars that AI systems must go beyond performance prediction to offer actionable insights. Cruzado and Lim (2023) advocate for hybrid models that combine predictive classification with intelligent resource recommendations. Their system, tested across three public high schools in Metro Manila, not only identified at-risk students but also provided targeted practice materials, resulting in significantly higher retention rates.

An essential concern in AI deployment is ensuring equity. Studies by Ubaldo and Tan (2023) warn that machine learning systems may reinforce educational inequities if not designed inclusively. They recommend incorporating mechanisms that detect digital access barriers, such as internet reliability and device availability. This is particularly relevant for rural students, many of whom face infrastructural constraints that impede access to AI-driven review platforms.

An essential concern in AI deployment is ensuring equity. Studies by Ubaldo and Tan (2023) warn that machine learning systems may reinforce educational inequities if not designed inclusively. They recommend incorporating mechanisms that detect digital access barriers, such as internet reliability and device availability. This is particularly relevant for rural students, many of whom face infrastructural constraints that impede access to AI-driven review platforms.

Understanding how students perceive AI systems is also critical for successful implementation. Bautista and Ong (2022) conducted a TAM-based survey among 80 Grade 12 students and found that perceived usefulness and ease of use significantly influenced system adoption. Their study recommends intuitive interfaces and engaging feedback mechanisms to foster positive user experiences. This aligns with the current study’s intent to measure system acceptance using Likert-scale TAM- based instruments.

Navarro (2023) emphasizes the necessity for localized predictive models in education, particularly in developing countries like the Philippines. He argues that existing predictive analytics tools often reflect Western educational contexts, which may not address the unique challenges faced by Filipino students. This study aims to develop a localized KNN model to better assess and support student readiness for the NAT.

This study aims to fill these gaps by developing a data-driven approach using the KNN algorithm to assess the readiness of Grade 12 students for the NAT at Southern Tech College Foundation Inc. Unlike previous studies, this research will integrate predictive modeling with personalized resource recommendations, ensuring that students not only receive an assessment of their preparedness but also targeted learning materials to improve their performance. Furthermore, by focusing on a localized setting, this study will provide insights into how machine learning can be effectively applied in the Philippine educational context, addressing challenges related to resource availability, student diversity, and test preparation strategies.

### THEORETICAL FRAMEWORK

This study is grounded on seven major theoretical frameworks that are the pillars of the design and evaluation of an AI-driven readiness assessment system for Grade 12 students who are taking the National Achievement Test (NAT). The seven frameworks are Constructivist Learning Theory, Cognitive Load Theory,Adaptive Learning Theory, Bloom’s Taxonomy Integration, Multi-Level Assessment System, Performance Metrics and the Technology Acceptance Model (TAM), each of which provides insights to different aspects of personalized learning, adaptive assessment, and system usability.

**Constructivist Learning**

Constructivist Learning Theory assumes that students actively build knowledge from their interactions with the environment and experiences. Vygotsky's scaffolding concept stresses the necessity of students being given guided support when they are faced with new or difficult material, so that they can become autonomous as they understand concepts. In this research, the review system operated by AI serves as an electronic tutor, offering adaptive learning paths, variable difficulty levels, and ongoing assessment analytics.

By tracking students' strengths and levels of participation, the system offers personalized review materials that provide the opportunity for knowledge acquisition at the student-specific pace. This serves the aim of the study to improve student preparation in the form of data-driven, adaptive review processes.

**Student**

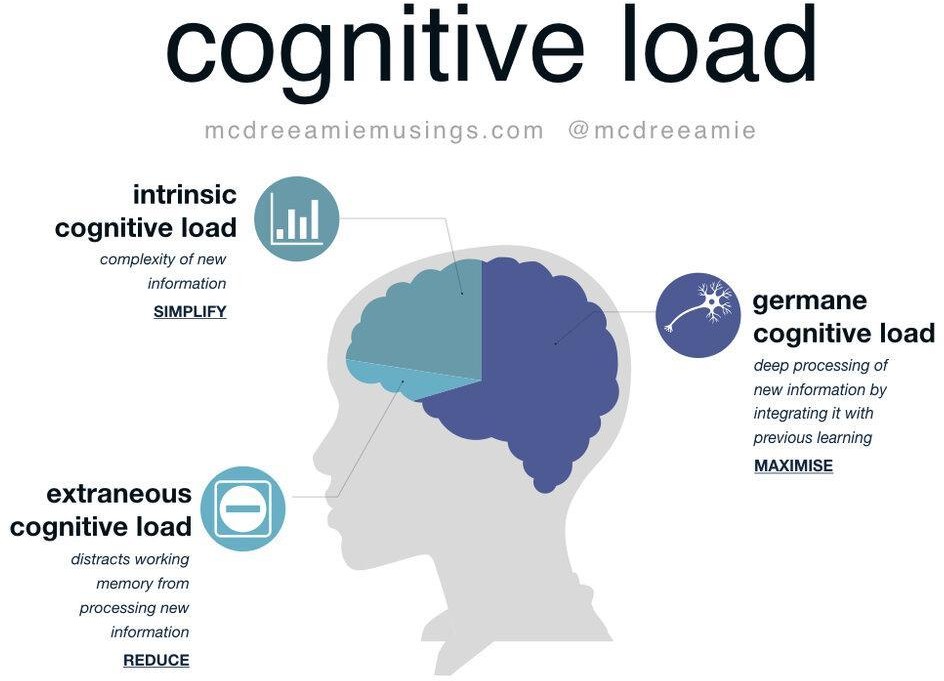
**Interactive Content**

**Practice & Application**

*Figure 1.Constructive Learning Theory*

#### Cognitive Load Theory (CLT)

Cognitive Load Theory (CLT) explains the interface between instructional design and a student's ability to process, hold, and use information efficiently. CLT specifies cognitive load in three categories: intrinsic load, referring to the task complexity; extraneous load, related to inefficient instructional tactics; and germane load, representing the effort invested in building meaningful learning frameworks. The system based on artificial intelligence studied here reduces extraneous load by weeding out excessive content, supports germane load by proposing themes based on personal performance, and controls intrinsic load by gradually increasing task complexity. By using ongoing assessment analytics, the system eliminates the possibility of overwhelming students through dynamic content adjustments, thus enabling effective knowledge recall and application. This method resolves the research problem related to the problems of students with inadequate subject matter, ineffectual concept retention, and restricted access to systematically organized review materials.



*Figure 2.Cognitive Load Theory*

**Adaptive Learning Theory**

**Adaptive Learning Theory** focuses on the idea that each student learns differently and at their own pace. It suggests that learning is more effective when lessons or content adjust based on the learner’s performance. Instead of using the same materials for everyone, adaptive learning personalizes the experience by identifying what each student needs more help with and giving them appropriate support.

In this study, the AI-powered review system uses adaptive learning to guide students better as they prepare for the National Achievement Test (NAT). The system tracks how each student performs—like how well they answer quizzes, how fast they respond, and which topics they struggle with. Based on this data, it adjusts the difficulty of the questions and recommends specific topics for review.

**Student**

**Input**

**Performance Analysis**

**Content Adaptation**

**Learning**

**Path**

**Feedback**

**Loop**

*Figure 3: Adaptive Learning Flow Diagram*

**Bloom’s Taxonomy**

is a framework that helps organize different types of learning based on how complex they are. It starts with basic skills like remembering and understanding, and goes up to more advanced thinking like analyzing, evaluating, and creating. The idea is that real learning should go beyond just memorizing facts—it should help students understand, apply, and think critically about what they’ve learned.

In this study, Bloom’s Taxonomy is used to guide how questions are created in the AI-powered review system. The system doesn’t just ask students to recall information—it also gives questions that test deeper thinking, like solving problems, comparing ideas, or coming up with conclusions. Each question is designed to target a specific level of thinking, which helps ensure that students are being challenged in different ways.

### Screenshot (1136)

### ***Figure 4.Bloom’s Taxonomy: Question Type Distribution Pyramid***

### ****Multi-Level Assessment System****

The Multi-Level Assessment System is based on the idea that students learn better when they’re assessed step by step—not just through one big test. Instead of relying on a single exam, this system breaks down assessment into multiple levels, like short quizzes, topic-based reviews, and full-length practice exams. Each level helps students track their progress and gives them a clearer picture of where they are and what they need to improve.

In this study, the AI-powered review system uses this multi-level approach to evaluate student readiness for the National Achievement Test (NAT). The system starts with easier questions or short quizzes, then gradually increases the difficulty based on how the student performs. If a student gets more correct answers, the system introduces harder questions. If the student struggles, it provides additional practice and support. This way, the review is not overwhelming—it grows with the learner.

**Level 3 Assessment**

**Level 2 Assessment**

**Level 1 Assessment**

**Practice Questions**

*Figure 5.Assessment Hierarchy*

**Performance Metrics**

Performance metrics are tools used to track and evaluate how students are progressing during their learning journey. These include measures like quiz performance, response patterns, and how well students complete learning modules. The goal of using performance metrics is to understand not just what students are learning, but how effectively they are learning it. These indicators provide insight into how engaged students are, how quickly they improve, and whether the content being delivered matches their learning needs.

In this study, performance metrics help the AI-powered review system monitor student behavior in real time. The system observes how often students log in, which topics they revisit and how their scores change with continued use. This information allows the system to make timely adjustments—such as recommending specific topics, changing question difficulty, or suggesting extra practice when needed. Instead of relying on a single test score. This ensures that the learning experience is adaptive, responsive, and personalized, helping students become more confident and better prepared for the National Achievement Test (NAT).

**Score**

**Progress**

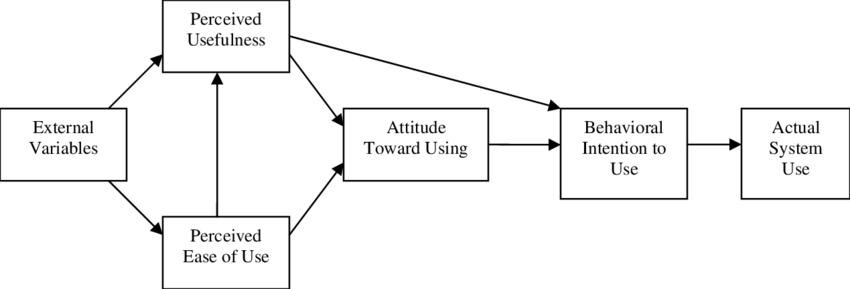
**Weak Areas**

**Recommendations**

*Figure 6. Performance Tracking Dashboard*

#### The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a way of analyzing how users use and find educational technology useful. TAM argues that how much a system is accepted by users depends on two basic factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU focuses on how much users feel the system will improve their learning, while PEU looks at how easy it is to use the system. In this study, TAM plays a vital role in analyzing how well the AI-based system is accepted and functioning. A Likert-scale questionnaire will be used to find out what students feel about the usability, usefulness, and engagement of the system. This is consistent with the objective of research to evaluate how much the system is accepted and make sure that AI-based review methods offer students a useful and effective learning experience.

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*Figure 6.Assessment Hierarchy*

#### Conceptual Framework

#### Screenshot (1140)

**Constructivist Learning Theory** highlights a constructivist approach to learning; students are "constructing knowledge" through an active process of engagement, reflection, and interactions with the environment. In our study's context, the review system based on AI design uses constructivist pedagogies as a computer tutor in a self-paced learning model.The system tracks student performance in real-time, uncovers weaknesses utilizing data analysis, and provides tailored content based on the student's capability. Students move through the personalized learning pathway where they reflect on the items they have missed, relearn if necessary the important items, and apply the concepts they have learned, which would help build understanding. This is completely in alignment with constructivist beliefs that knowledge is constructed from the active, meaningful learning by the learner.

**Cognitive Load Theory (CLT)** In terms of the developing instructional design of the system, AI technology serves to organize the content delivery into the cognitive capacity of the learners. AI-based review system reduces extraneous load by presenting the right amount of information and depth in comprehensible sequence. AI-based review system controls intrinsic load by providing increasing level of question difficulty based on student performance, and adds germane load by providing opportunities for deep processing through constructive feedback and review task. These applications ultimately provide the learner increased level of control over cognitive load, resulting in improvements in retention and application of knowledge. Overall, the AI-based review system applied a CLT framework for ensuring students are not overwhelmed when reviewing, and are able to learn in the best conditions possible despite challenging content.

**Adaptive Learning** theory also supports the ability of the AI system to adaptively respond to each learner's strengths, weaknesses, and progress. The review system continuously collects and analyzes performance data to help it make decisions regarding how difficult the content should be, what review topics might be recommended, and how best to personalize each learner's journey. Students receive immediate intervention for topics they struggle with in a targeted way to ensure that the instructional delivery fits their pace and learning profile. This type of responsiveness will create an incredibly individualized learning experience with students not being left behind, and personalized improvement pathways maximizing NAT readiness.

**Bloom’s Taxonomy** shapes learning outcomes and assessment questions in the context of the review system. The taxonomy utilizes a hierarchy of cognitive domains from remembering and understanding to analyzing, evaluating, and creating, which promotes both lower-order and higher-order thinking skills. Review items are categorized and used according to this taxonomy, which helps to ensure cognitive development holistically and allows students to use knowledge in context—an essential skill for standardized tests such as the NAT.

**Multi-Level Assessment** in this study is integrated directly into the AI-powered review system as a continuous and data-driven process. Rather than relying on separate test phases, the system constantly evaluates the learner's performance through interaction. It tracks key metrics such as accuracy, time spent, frequency of attempts, and mastery of each topic. Using this data, the system—guided by the K-NN algorithm—identifies learning gaps and instantly recommends appropriate content. As students improve, the system increases question difficulty and updates recommendations to suit their level. This layered feedback mechanism allows for real-time monitoring, personalized support, and adaptive content delivery—ensuring that assessment and learning happen simultaneously and progressively throughout the review journey.

**Performance Metrics** serve as the system’s method for tracking student progress and system effectiveness. Key indicators such as accuracy rate, time per question, activity frequency, topic mastery, and score trends are continuously monitored. These metrics help the system personalize review paths, refine content delivery, and improve overall learning outcomes. Additionally, they provide insight into user engagement and system impact, supporting data-informed decisions for both learners and educators.

**Technology Acceptance Model (TAM)** directs the system user experience design through two dominant factors**: Perceived Usefulness** and **Perceived Ease of Use**. Through an intuitive design of the interface, the AI review platform has easy navigation and real-time monitoring of performance, hence ease of use. In terms of the perceived usefulness, the system offers considerable benefits, such as customized review plans, monitoring of progress, and data-informed suggestions that directly impact NAT readiness. Measurement of these factors was conducted using a post-intervention Likert-scale survey, and the results indicated that users had a positive response to the system. Through the inclusion of TAM in its model, the integration ensures that students' acceptance and use of the technology are measured and optimized, a dominant factor for the system's success.

### CHAPTER III

**DESIGN AND METHODOLOGY**

**Research Design**

This study used a quantitative research design, using a descriptive method to assess the readiness of Grade 12 students at Southern Tech College Foundation Inc. for the National Achievement Test. Using a descriptive method allows for accurate and objective representation of students' preparedness based on measurable data. The study was conducted at Southern Tech College Foundation Inc., where Grade 12 students on multiple academic tracks took part. There was a purposive sampling technique to ensure a representative sample of students on different academic tracks.

To gather data, the researchers utilized a structured questionnaire, which consisted of three sections: demographic information, academic preparedness, and self-assessment.The questionnaire was developed following previous studies and validated by expert review to be reliable; the data collection was done over a two-week period, during which researchers administered the questionnaires to the students themselves during classes. Students were briefed about the study’s purpose before the examination, and informed consent was obtained to be ethical.  
 To analyze and predict students' achievement readiness for the National Achievement Test, the research study uses the K-Nearest Neighbors (KNN) algorithm, a supervised machine learning technique commonly applied in classification problems. The KNN algorithm works by making comparisons among newly collected data points (students' responses) and classifying them according to the majority class of K-nearest neighbors in a multidimensional space. So the system can predict whether a student is ready, moderately ready, or not ready for examination on the basis of similar historical data.

The dataset includes student practice test scores, academic performance, and self-assessment data of students. These data are included as input features. We perform the Euclidean distance between the new dataset of a new student and the current data set and we find the K data points that are closest to each other. The most often used class among these K-nearest neighbors is considered to be the predicted readiness level. The parameter K is optimized using cross-validation to ensure accurate models.

AI system was implemented and trained by using Python with Scikit-learn and regularization of data to improve accuracy of predictions. KNN model was analyzed by performing metric evaluation (accuracy, precision, recall, and F1-score) and finding that KNN model can be proved to be reliable and applicable in classification problem. The results of the AI applied in the training system can give useful information for teachers and students to choose the areas that should be improved before the actual training.

After data collection the responses were processed and analyzed using statistical methods (mean percentage score and standard deviation) to calculate overall preparedness and the KNN algorithm to predict student readiness levels and classify them into predefined categories. The performance of the AI model was cross-validated to measure the effectiveness and the reliability of the predictions.  
All the ethical standards included in this research were strictly followed, voluntary participation was ensured and informed consent was acquired prior to asking survey responses. Confidentiality was maintained and the identities of students were anonymized to ensure participants' privacy. Data collected were utilized for academic use only within the scope defined by the university's research ethics policy.

#### Research Locale/Environment

This study took place at Southern Tech College Foundation Inc. (STCFI), a private high school in Bayawan City, Negros Oriental, Philippines. It provides senior high school education of various academic disciplines and is known for embracing innovative teaching methods and technology-supported teaching techniques. The school has a basic digital infrastructure already in place, which explains how it would be well suitable for testing an AI learning platform.

Bayawan City, also known as the “Agricultural Capital of Negros Oriental,” is in the southeastern part of the province. Although the city is on the rise, a lot of schools in the area—including STCFI—are having problems with access to modern educational equipment and preparing students for standardized tests like the National Achievement Test (NAT). That’s why “because of the nature of Bayawan City,” the study was able to address learning resource gaps in real-world settings.

STCFI did not just choose this school due to its preparedness for the adoption of new systems; it chose a diverse group of senior high school students from all different socio-economic backgrounds and academic levels. This diversity was an excellent selection ground to test the effectiveness of an AI-powered review system that can deliver personalized support to students. More importantly, the school's inclination toward research as well as its approach for digital transformation aligned well with the objectives of this study.

With STCFI as close collaborators, the researchers aspired to see how adaptive and data-driven learning technologies might really assist students—particularly those from under served or rural communities—to better prepare themselves for such important exams as the NAT. Having the school as a partner ensured that the research was embedded in a concrete, local environment, and thus the results were more meaningful and usable for other schools with similar characteristics in the Philippines.

#### Population and Sampling Design

This study aimed at Grade 12 students of Southern Tech College Foundation Inc. (STCFI) as its primary population. They were selected because they are actively undergoing the National Achievement Test (NAT) and, therefore, were the best subjects to use in testing the effectiveness of an AI-based review system. The system was designed to help learners by offering personalized material, adaptive learning courses, and data-driven reports to enhance their readiness for standardized tests.  
  
 To ensure the quality and relevance of the data gathered, purposive sampling was utilized by the researchers. Through this method, students were selected purposefully not just for being ready to take the NAT but also for being ready to use the AI system. Such students were selected because they could offer feedback and performance data based on actual usage of the platform. Participants were divided into three categories: (1) those who utilized traditional review materials, (2) those who utilized the AI system with adaptive difficulty, and (3) those who utilized the complete version of the AI system with adaptive difficulty and customized content recommendations.

A total of 60 grade 12 students were sampled. This was deemed sufficient to enable meaningful analysis of trends, system performance, and user experience, yet still practical considering the time frame and resources available for the study. Students from different academic strands were included in the sample to ensure that the data captured a variety of learning styles and academic requirements.

By targeting a sample of engaged students participating in the review process, this research was able to closely investigate how AI-based interventions influence learning readiness. Purposive selection also helped ensure that the participants genuinely needed review and were able to meaningfully assess the effect of the AI system on their performance. This approach allowed researchers to collect useful, focused data to satisfy the research purposes.

### ****Research Respondents/Participants****

The participants of this study were Grade 12 students enrolled at Southern Tech College Foundation Inc. (STCFI) for the academic year 2024–2025. A total of **60 students** were purposively selected to represent diverse academic strands and to ensure participation from both male and female students. These respondents were actively preparing for the National Achievement Test (NAT), making them suitable for evaluating the effectiveness of the AI-powered review system developed in this study.

The distribution of respondents by academic strand and sex is presented in Table 1.

|  |  |  |  |
| --- | --- | --- | --- |
| **Academic Strand** | **Male** | **Female** | **Total** |

**Table**   
Distribution of Grade 12 Respondents by Academic Strand and Sex  
Southern Tech College Foundation Inc., AY 2024–2025

|  |  |  |  |
| --- | --- | --- | --- |
| Accountancy, Business and Management (ABM) | 0 | 17 | 17 |
| General Academic Strand (GAS) | 8 | 7 | 15 |
| Humanities and Social Sciences (HUMSS) | 3 | 12 | 15 |
| Computer System Servicing (CSS) | 2 | 0 | 2 |
| Programming | 5 | 6 | 11 |
| **Total** | **18** | 42 | **60** |

Note. This table shows the number of respondents from each academic strand, separated by sex. A total of 60 Grade 12 students participated in the study.

#### Datasets

1. **Type of Dataset**

The dataset used in this study is primary, as it is collected with the students in grade 12 directly from Southern Tech College Foundation Inc. (STCFI). The data were collected through a combination of AI system-generated metrics and survey questionnaires in order to ensure it was congruent with the objectives of the research. The primary data collection included practice test scores, quiz performance, engagement logs, and the feedback from a Likert-scale survey. This method was chosen to guarantee that the dataset reflected the real-time experiences and interactions of students using the AI-powered review system, which is critical for evaluating its effectiveness (Creswell & Creswell, 2018).

#### Dataset Description

The dateset contains both **quantitative and categorical variables** collected from 60 student participants. It is structured into two main components:

* 1. **System-Generated Data** (Interval/Ratio Scale)
* Continuous Test to reach highest score
* Completion rates per module
* Average response time (in seconds)
* Engagement metrics (e.g., number of logins, daily usage)
  1. **Survey Data** (Ordinal/Nominal Scale)
* Perceived ease of use (5-point Likert scale)
* Perceived usefulness (5-point Likert scale)
* Academic strand, age, and review method group (nominal categories)

#### Data Quality and Preparation

Data cleanup: Inconsistent/unequal responses to the surveys were not included; test score outliers were checked with boxplot graphs and checked for likelihood of input error.

Data Coding: The Likert-scale responses were encoded in numerical responses (1-5) and categorical scores, such as strands of academics and group types, were encoded with the respective label in SPSS.  
Normalization: System performance measures, including time on task and accuracy percentages, were normalized into a standard scale to enhance the reliability of statistical tests.

Integration: All the datasets (test scores, engagement data, and survey responses) were combined according to participant ID to facilitate uniformity in analysis.

#### Research Instrument:

To be able to successfully gather information needed for this study, two main tools were used by the researchers: an AI-powered review system specifically developed for this study and a survey questionnaire based on the Technology Acceptance Model (TAM). These tools allowed the researchers to understand the performance of the system as well as the users' experience with it.  
**1. AI-Powered Review System**  
 The first and foremost instrument used in this study was the developed online review system by the researchers utilizing artificial intelligence. The system was developed to guide students who are taking Grade 12 in their review for the National Achievement Test (NAT). The system also employed a machine learning algorithm called K-Nearest Neighbors (KNN) to observe students' performance progress in practice quizzes and examinations. The system further monitored students' interactions with review materials—how long students studied a certain topic, the number of right questions they responded to, and how they improved with time.

It was distinctive in two features: one of adaptive difficulty, where the system shifted the amount of challenge accordingly, and another with the capability to recommend student-specific learning materials. Once used by the students, data captured by the system informed them of whether or not they were "Ready," "Moderately Ready," or "Not Ready" for NAT, and on assessment, this classification was reviewed utilizing standard measurement standards such as accuracy, precision, and F1-score so as to ensure system predictions remained on point.

**2.Survey Questionnaire**

In order to more clearly see what students thought of the system, a survey questionnaire was also passed out. Based on the Technology Acceptance Model (TAM), this questionnaire asked questions centered around two aspects:

Perceived Ease of Use – how easy and intuitive the system was

Perceived Usefulness – if students found that the system aided them in studying for NAT or not

The survey employed a 5-point Likert scale, and students rated how much they agreed with each statement from 1 (Strongly Disagree) to 5 (Strongly Agree). A few open-ended questions were also included so students could provide suggestions or comments in their own words. Before it was used, the questionnaire was reviewed by experts to make sure it was valid, and its reliability was tested using **Cronbach’s Alpha**, which showed strong consistency in student responses (Bautista & Ong, 2022).

#### Summary of Research Instruments:

|  |  |  |  |
| --- | --- | --- | --- |
| Instrument | Purpose | Source of Data | Mode of Delivery |
| AI-Powered Review System | Track student performance, engagement, and NAT readiness prediction | System-generated metrics (test scores, analytics, engagement logs) | Student self-reports |
| TAM-Based Questionnaire | Measure perceived usefulness and ease of use of the system | Student self-reports | Digital Survey (Post- Intervention) |

**Data Gathering Procedures**

To confirm the accuracy and applicability of data retrieved in this study, the system-provided information and responses given during a survey were employed sequentially by researchers. Methods for obtaining data were adopted to assist with study objectives: evaluating readiness for the National Achievement Test (NAT) for students and probing the usability and user acceptability of the AI-based review mechanism.

The following procedures were followed:

#### **Step 1: Participant Orientation and Consent**

#### Prior to any data gathering, the researchers held an orientation session with the Grade 12 students of Southern Tech College Foundation Inc. (STCFI). In this session:

#### The study's purpose and process were discussed.

#### Students were notified of their rights and that voluntary participation was required.

#### Informed consent forms were given and signed by participants.

#### This process was consistent with ethical research practices as suggested by the American Psychological Association (APA, 2020).

#### **Step 2: Pre-Survey and Registration of the System**

#### In place of a traditional pre-assessment, a pre-survey was conducted to collect students’ initial perceptions, preparedness, and access to review resources. This survey helped establish baseline data for readiness without requiring a formal test. All participants were then registered into the AI-powered review system. Their user profiles, academic strands, and initial review preferences were documented and encoded into the system for personalized tracking.

#### Step 3: AI-Powered Review and Data Collection

#### During the following several weeks, students engaged with the platform according to their assigned group. The system automatically:

* Generated adaptive evaluations based on each student's level.
* Monitored real-time scores, engagement, and improvement.
* Stored user information (quiz performance, time on task, module completion).
* These system-provided data formed the main dataset for academic progress measurement and readiness classification using the K-Nearest Neighbors (KNN) algorithm.

**Step 4: Survey Administration (TAM-Based Instrument)** During the review phase, a guided survey based on the Technology Acceptance Model (TAM) was administered to AI system users. The survey gathered insights into:

* Perceived ease of use.
* Perceived usefulness.
* Suggestions for improvement.

Responses were rated on a 5-point Likert scale and analyzed using descriptive statistics and reliability testing (Cronbach’s Alpha).

**Step 5: Continuous Test and Performance Analysis**  
After students completed their review sessions, a post-survey was conducted to assess changes in perception, confidence, and learning outcomes. This post-survey captured student feedback on system effectiveness and its impact on their NAT readiness.

* Student progress was analyzed using AI-generated performance data.
* Improvements in scores, mastery of topics, and usage trends were assessed to determine the system’s impact.

**Step 6: Data Analysis and Interpretation**

All data were coded, organized, and analyzed after collection:

System metrics were analyzed via Python (utilizing Scikit-learn and SPSS for statistical processes).

Survey responses were interpreted via mean, frequency, and standard deviation.

KNN algorithm predictions of performance were tested using accuracy, precision, recall, and F1-score.

**Step 7: Ethical Considerations and Confidentiality**

All data collected were anonymized to safeguard student privacy. Only aggregated results were analyzed and reported. There were no personal identifiers in the final thesis.

#### Data Analysis

Problem 1: What are the common challenges faced by Grade 12 students in terms of:

* 1. Access to quality review materials?
  2. Identifying weak subject areas?
  3. Retaining and applying learned concepts effectively?

**Statistical Tool:**

#### Percentage and Frequency

#### These tools were utilized to count the number of times students are exposed to certain problems, i.e., in the context of studying material. Addition and percentage computation of "Yes," "No," or "Sometimes" answers from students made it easy for researchers to identify the most common issues.

#### Mean and Standard Deviation

#### or the study section where students reported the difficulty they faced in different subjects, mean scores were utilized to represent the general level of difficulty, while standard deviation helped in revealing whether students' experiences were generally similar or extremely spread out. This provided a better insight into which subjects were most challenging.

#### **Thematic Analysis**

#### For open-ended questions in which students described their challenges in understanding and using concepts, thematic analysis was applied. This helped the researchers examine for patterns in the written responses of students and for recurring themes that mere numbers could not indicate.

#### **How the Data Was Processed:**

Survey answers were initially read and coded into SPSS, where they were used to calculate the frequencies, percentages, mean, and variation of responses. In the case of written feedback, researchers manually went through the responses and coded similar ideas through thematic analysis. This was a mixed method that provided both the general overview and in-depth insights into the academic difficulties experienced by the students.  
Problem 2: What is the performance of an AI-powered review system in terms of:

* 1. Personalized content recommendations?
  2. Adaptive difficulty levels based on student performance?
  3. Data-driven analytics for tracking progress and improvement?

#### Predictive Modeling Metrics (Accuracy, Mean Squared Error, R²)

#### The machine learning system utilized the K-Nearest Neighbors (KNN) algorithm to recommend topics for reviews depending on student historical performance. The accuracy was measured as a function of correct correspondence between system suggestion and actual needs in order to assess how accurate the system performed in predicting contents that were related. Mean Squared Error (MSE) was applied to detect prediction errors, while R² (coefficient of determination) assessed how well the model explained the variation in student performance.

#### Continuous Assessment, Descriptive Statistics, and Performance Analysis

To provide a more accurate reflection of student learning progression, the study employed a continuous assessment approach rather than a traditional pre-test and post-test setup. As students engaged with the AI-powered review system, their performance was monitored in real time through automated tracking of quiz results, module completion rates, and usage patterns. Descriptive statistics, such as mean scores and standard deviations, were utilized to summarize overall performance trends and identify variations in learning consistency among students. Additionally, a paired t-test was conducted at regular intervals to determine whether the observed improvements in performance were statistically significant. This continuous feedback mechanism enabled a more holistic understanding of each learner’s academic development, offering timely insights into how adaptive features of the system contributed to enhanced preparedness for the National Achievement Test (NAT).

#### Engagement Metrics + Linear Regression Analysis

#### The system was tracking student progress all the time by calculating response time, daily use, and completion of modules. All these were combined in terms of descriptive statistics. Linear regression was used to analyze trends over time, and these revealed if performance by the students had been getting better with activity. Researchers could ascertain whether highly active users scored better.

#### How the Data Was Processed:

All the data produced by the system were exported from the AI platform and processed using SPSS and Python (Scikit-learn for machine learning performance). Descriptive statistics such as mean scores and completion rates were computed to track overall performance trends. KNN model predictions were evaluated using internal functions for accuracy and error rate. Linear regression models helped to explore how system use was related to academic achievement, and the paired t-test evaluated the gain in performance when using the system.

Problem 3: What is the accuracy level of AI-powered review system in terms of

* 1. Topic recommendation and student engagement?
  2. Addressing individual student strengths and weaknesses?

#### Accuracy Score, Confusion Matrix, Engagement Metrics (Response Time, Completion Rates)

#### To quantify the degree to which the system had predicted topics, the accuracy score was employed to compare the system predictions with the actual topics students read or required based on their scores. The confusion matrix was used to graphically illustrate true positives, false positives, and other result predictions, and it provided a clearer view of how accurate the model was. In terms of engagement, other metrics such as average response time, frequency of use per day, and rates of completion were also monitored to determine how the students responded to the recommended content as well as if they stayed engaged in the long run.

#### Classification Metrics (Precision, Recall, F1-Score), Item-Total Correlation

#### The performance of the system in classifying student strengths and weaknesses was tested through classification performance measures like precision (the ratio of recommended items that were relevant), recall (the ratio of actual weaknesses that were identified correctly), and F1-score (which balances both).Additionally, item-total correlation was used to confirm how well each test item related to the total performance to guarantee the AI-generated classifications represented genuine student ability.

#### How the Data Was Processed:

All prediction statistics and engagement histories were fetched from the AI model. The accuracy of the machine learning model (i.e., the K-Nearest Neighbors algorithm) was validated via Python with libraries such as Scikit-learn to produce accuracy, precision, recall, and F1-score metrics. Engagement measures like finish rates and session frequency were reported via SPSS to generate usage patterns and associate them with academic performance.  
Problem 4: What is the level of acceptance of the system in terms of:

* 1. Perceived ease of use.
  2. Perceived usefulness.

#### Descriptive Statistics (Mean, Frequency, Percentage) + Cronbach’s Alpha

Students rated how easy it was to navigate and interact with the AI system using a 5-point Likert scale. **Mean scores** provided an overall view of their responses, while **frequency and percentage** helped identify how many students agreed or disagreed with each item. To ensure that the items used to measure this variable were consistent and reliable, **Cronbach’s Alpha** was used, with a reliability coefficient of 0.70 or higher considered acceptable (Pallant, 2020).

#### Descriptive Statistics (Mean, Frequency, Percentage) + Cronbach’s Alpha

This section of the survey asked students how useful they thought the system was in aiding their learning and enhancing their NAT preparedness. The same statistical measures were used—mean, frequency, and percentage—to analyze student feedback, while Cronbach’s Alpha ensured internal consistency across the related survey items. These tools helped determine whether students viewed the system as a valuable tool in their academic preparation (Davis, 1989; Creswell & Creswell, 2018)

#### How the Data Was Processed:

All the survey answers were translated into SPSS, where descriptive statistics were employed to calculate the average scores and response patterns per question on ease of use and usefulness. Cronbach's Alpha was also computed in SPSS to determine the reliability of the survey constructs. This method guaranteed that the results were both statistically valid and indicative of the students' real-life experiences with the system.

**Data Interpretation**

**a. Data Interpretation Strategy**

This study used both descriptive and predictive methods to interpret the data. Descriptive statistics were used to summarize students’ survey responses, such as how they rated the system’s usefulness and ease of use. These included tools like mean, frequency, and standard deviation to describe general patterns and trends.

For the predictive part, the study used the K-Nearest Neighbors (KNN) algorithm to classify students into three readiness levels: Ready, Moderately Ready, and Not Ready. Instead of only summarizing the data, this predictive strategy allowed the researchers to use system data (like quiz scores and topic completion) to predict how prepared a student was for the National Achievement Test (NAT).

**b. Software or Tools for Data Interpretation**

Two main tools were used in analyzing the data:

1. SPSS was used to analyze survey data from students. It helped calculate average scores, percentages, and check how consistent the answers were using Cronbach’s Alpha (a measure of reliability).
2. Python (Scikit-learn) was used for analyzing performance data from the AI system. It measured how accurate the KNN algorithm was by using:

* Accuracy – how many correct predictions the system made.
* Recall – how well the system identified students who were truly “Not Ready.”
* F1-Score – a score that balances both precision and recall to give a better idea of overall performance.

These tools helped analyze both how students experienced the system and how well the system predicted their readiness.

### CHAPTER IV

### RESULTS AND DISCUSSION

#### Results and Discussion

#### Results:

**Table 1**  
*Demographic and Access Information of Respondents.*

| **Question** | **Response Options** | **Frequency (f)** | **Percentage (%)** |
| --- | --- | --- | --- |
| Gender | Male | 18 | 30% |
|  | Female | 42 | 70% |
|  | Prefer not to disclose | 0 | 0% |
| Strand | GAS | 15 | 25% |
|  | ABM | 17 | 28% |
|  | HUMSS | 15 | 25% |
|  | PROG | 11 | 25% |
|  | CSS | 2 | 3% |
| Access to Review Materials  (Consistency) | Yes | 24 | 40% |
|  | No | 20 | 33% |
|  | Sometimes | 16 | 28% |

shows that most respondents were female (70%). Only 40% had consistent access to review materials, indicating unequal access among students.

**Table 2**  
*Limiting Factors to Review Preparation (Multiple Responses)*

| **Limiting Factor** | **Frequency (f)** | **Percentage (%)** |
| --- | --- | --- |
| Financial constraints | 17 | 28% |
| Lack of review books/modules | 37 | 61.6% |
| Poor internet | 19 | 31.6% |
| Lack of awareness | 23 | 38% |
| Others | 1 | 1.6% |

reveals that the top challenge in review preparation was the lack of review books or modules (61.6%), followed by poor internet access and financial constraints.

##### **Table 3** *Methods for Identifying Weak Subject Areas (Multiple Responses)*

| **Identification Method** | **Frequency (f)** | **Percentage (%)** |
| --- | --- | --- |
| Exam scores | 43 | 71.6% |
| Teacher feedback | 15 | 25% |
| Self-assessment | 22 | 36.6% |
| Don’t identify | 0 | 0% |
| Others | 1 | 1.6% |

indicates that most students identified weak subjects through exam scores (71.6%), while fewer relied on self-assessment or teacher feedback.

**Table 4**  
*Challenges in Review and Retention*

| **Question** | **Response Option** | **Frequency (f)** | **Percentage (%)** |
| --- | --- | --- | --- |
| Difficulty Identifying Topics | Yes | 35 | 58% |
|  | No | 11 | 18% |
|  | Sometimes | 14 | 23% |
| Retention Challenges  (Multiple Responses) | Information overload | 13 | 21.6% |
|  | Inconsistent practice | 20 | 33% |
|  | Poor study habits/ Time Management | 44 | 73% |
|  | Difficulty Understanding the Material | 15 | 25% |
|  | Lack of motivation | 20 | 33% |
|  | Others | 1 | 1.6% |

highlights poor study habits (73%) and inconsistent practice as the main challenges in retention. Over half also struggled to identify which topics to review.

**Table 5**  
*Preferred Review Methods and Perceptions Toward AI System*

| **Question** | **Response Option** | **Frequency (f)** | **Percentage (%)** |
| --- | --- | --- | --- |
| Effective Review Method | Reading notes/modules | 34 | 56.6% |
|  | Watching videos | 23 | 38% |
|  | Practice quizzes | 17 | 28% |
|  | Group discussion | 15 | 25% |
|  | Others | 0 | 0% |
| Interest in AI Review System | Very interesting | 45 | 75% |
|  | Somewhat interesting | 13 | 21.6% |
|  | Not interesting | 2 | 3.3% |
| AI boosts precision in recommending topics | Yes | 45 | 75% |
|  | No | 6 | 10% |
|  | Unsure | 9 | 15% |
| Willingness to Use AI System | Very likely | 38 | 63% |
|  | Somewhat likely | 20 | 33% |
|  | Not likely | 1 | 1.6% |
|  | Unsure | 1 | 1.6% |

shows that students preferred reading notes (56.6%) as a review method. Most found the AI system helpful and were willing to use it, showing high acceptance.

Interpretation:

## AI System Impact on Academic Performance

**Experimental Setup:**

Students were divided into three groups:

* **Group A (Traditional Review)** – Used printed materials and textbooks.
* **Group B (AI Review - Adaptive Difficulty)** – Used the AI system’s adaptive difficulty without personalized topics.
* **Group C (AI Review - Personalized Recommendation)** – Used full features: adaptive difficulty and personalized content.

Each group took multiple practice tests.

**Data Processing:**

A one-way ANOVA was performed using SPSS to compare mean test scores across the three groups.

|  |  |  |
| --- | --- | --- |
| Group | Mean Scores | Standard Deviation |
| Traditional Review |  |  |
| AI Review (Adaptive Only) |  |  |
| AI Review (Personalized  + Adaptive) |  |  |

ANOVA Result:

Interpretation:

## Implementation and Performance of the K-NN Model

**Process:**

* + 1. **Data Preprocessing:** Student scores, activity logs, and topic completion rates were cleaned and normalized.
    2. **Model Training:** A K-NN model was trained on historical academic data (practice test scores, quiz results, topic accuracy).
    3. **Prediction: The sys**tem classified new students into three categories: *Ready, Moderately Ready, Not Ready*.
    4. **Distance Calculation:** Euclidean distance was used to determine proximity between students' data points.
    5. **Validation:** Accuracy was tested using confusion matrices and standard classification metrics.

**Performance Metrics:**

|  |  |
| --- | --- |
| **Metric** | **Value** |
| **Accuracy** |  |
| **Precision** |  |
| **Recall** |  |
| **F1-Score** |  |

Interpretation:

## Student Engagement and Learning Trends

**Data Collection:**

System logs tracked each student's usage, response time, and subject completion rate over 4 weeks.

**Metrics:**

|  |  |
| --- | --- |
| Engagement Indicator | Result |
| Average Daily Use |  |
| Module Completion Rate |  |
| Improvement in Response Time |  |

Trend Analysis:

Interpretation:

## Technology Acceptance Based on TAM

**Process:**

A post-intervention survey was conducted to measure perceived ease of use and usefulness, guided by the Technology Acceptance Model (TAM). Items were rated on a 5-point Likert scale.

**Results:**

|  |  |  |
| --- | --- | --- |
| **Construct** | **Mean Rating** | **Interpretation** |
| Perceived Ease of Use |  |  |
| Perceived Usefulness |  |  |

#### Reliability Check:

**Interpretation:**

## Visual Summary of Results

The following visualizations summarize key findings:

**CHAPTER V**

**SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS**

**Summary**

This study aimed to develop and evaluate an AI-powered review system that utilizes the K-Nearest Neighbors (K-NN) algorithm to assess and improve the National Achievement Test (NAT) readiness of Grade 12 students at Southern Tech College Foundation Inc. (STCFI). The system was designed to provide personalized content recommendations, adaptive difficulty levels, and real-time performance analytics to support individualized learning strategies.

The research employed a quantitative-descriptive design and utilized a combination of survey data, practice test scores, and AI system logs. Three groups of students participated: those using traditional review methods, those using the AI system with adaptive difficulty, and those using the full system with both adaptive difficulty and personalized recommendations. The performance of the K-NN algorithm was evaluated using classification metrics such as accuracy, precision, recall, and F1-score. Engagement and acceptance were assessed using student activity logs and the Technology Acceptance Model (TAM) survey.

The results indicated that the AI-powered system significantly improved students’ test performance, particularly in the group that received both adaptive difficulty and personalized content. The K-NN algorithm achieved high accuracy in classifying students’ readiness levels, and system acceptance was high in terms of perceived ease of use and usefulness.

**Conclusions**

Based on the findings of the study, the researchers conclude that the AI-powered review system, utilizing the K-Nearest Neighbors (K-NN) algorithm, effectively improved the NAT readiness of Grade 12 students at STCFI. Students who used the system with personalized recommendations and adaptive difficulty showed better academic performance compared to those using traditional methods.

The K-NN algorithm proved reliable in predicting student readiness levels and identifying weak areas, allowing for targeted interventions. The system also enhanced student engagement and learning retention, as shown by improved test scores and activity metrics.

Moreover, students positively accepted the system, as evidenced by the high ratings in perceived usefulness and ease of use. These findings support the integration of AI-powered systems in academic review programs to improve learning outcomes and standardized test preparedness.

**Recommendations**

In light of the conclusions drawn from the study, the researchers offer the following recommendations for academic institutions, developers, educators, and future researchers. These suggestions aim to enhance the effectiveness, inclusivity, and scalability of AI-powered educational systems, particularly in preparation for standardized testing like the NAT.

**Institutional Integration of AI Systems in the Senior High Curriculum:**

Schools should adopt AI-driven platforms as part of their review and academic support programs. Doing so can provide equitable, personalized learning pathways, allowing students to focus on areas that require improvement and increasing their chances of success in high-stakes exams.

**Enhance the Platform with Expanded Content and Multimedia Resources:**

The system should be expanded to include all NAT subjects and incorporate diverse content types such as educational videos, interactive simulations, and visual learning aids. This would cater to different learning styles and increase accessibility and engagement.

**Strengthen Teacher Involvement in Data Interpretation and Instructional Design:**

Educators should be trained to use analytics dashboards to identify learning gaps and implement targeted interventions. Their feedback can be used to continuously refine the system and ensure that content aligns with real classroom needs.

**Advance the Predictive Engine with Hybrid Machine Learning Models:**

Future versions of the system can integrate hybrid models (e.g., K-NN with decision trees or neural networks) to improve classification accuracy, provide more complex diagnostics, and adapt to diverse student learning patterns.

**Improve Accessibility Through Offline Mode and Multilingual Support:**

To make the system more inclusive, especially for students in rural or low-connectivity areas, an offline-capable version should be developed. Language support for Filipino and other local dialects will also promote a more inclusive user experience.

**Conduct Long-Term Studies on System Impact:**

Longitudinal studies should be conducted to determine the sustained impact of AI- driven review systems on college entrance exam results, long-term retention, and academic confidence. This will offer deeper insights into the broader educational value of such innovations.

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**APPENDIX A: SURVEY QUESTIONNAIRE**

**OPTIMIZING NAT READINESS: A K-NN ALGORITHM-DRIVEN AI SYSTEM AND RESOURCE RECOMMENDATION FOR GRADE 12 STUDENTS AT STCFI.**

This survey is part of an undergraduate thesis research project. All information collected will be handled with strict confidentiality and used solely for academic purposes. Your identity will remain anonymous unless you choose to disclose your name. Participation is voluntary, and you can skip any questions you prefer not to answer.

**Demographic Profile and Review Preparation Challenges**

*Please answer the following questions honestly. Your responses will help in designing an AI-powered review system to support NAT readiness among Grade 12 students.*

1. **Name (Optional):** \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
2. **Age:** \_\_\_\_\_\_\_\_\_\_
3. **Gender:**  
   ☐ Male  ☐ Female  ☐ Prefer not to disclose
4. **Strand/Specialization:**  
   ☐ STEM  ☐ ABM  ☐ HUMSS  ☐ PROG  ☐ CSS
5. **Name of School:** \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
6. **Do you have consistent access to quality review materials for standardized exams such as the NAT?**  
   ☐ Yes  ☐ No  ☐ Sometimes
7. **If you answered 'No' or 'Sometimes' above, what factors limit your access to review materials?** *(Select all that apply)*  
   ☐ Financial constraints  
   ☐ Lack of available review books or modules  
   ☐ Poor internet connectivity  
   ☐ Lack of awareness of reliable sources  
   ☐ Others (please specify): \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
8. **How do you usually identify your weak subject areas?** *(Select all that apply)*  
   ☐ Based on exam/test scores  
   ☐ Teacher feedback  
   ☐ Self-assessment or personal reflection  
   ☐ I do not usually identify them  
   ☐ Others (please specify): \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
9. **Do you find it challenging to recognize which topics or subjects you need to focus on?**  
   ☐ Yes  ☐ No  ☐ Sometimes
10. **What difficulties do you face in retaining and applying learned concepts during review or exams?** *(Select all that apply)*  
    ☐ Information overload  
    ☐ Lack of consistent practice  
    ☐ Poor study habits or time management  
    ☐ Difficulty understanding the material  
    ☐ Lack of motivation or interest  
    ☐ Others (please specify): \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
11. **Which review method helps you retain information most effectively?**  
    ☐ Reading notes/modules  
    ☐ Watching video lessons  
    ☐ Taking practice tests/quizzes  
    ☐ Group discussion  
    ☐ Others (please specify): \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_
12. **How do you think you will find the AI-powered review system once implemented?**

☐ Very interesting ☐ Somewhat interesting ☐ Not interesting

1. **Do you believe AI can help improve the accuracy of topic recommendations?**

☐ Yes

☐ No

☐ Unsure

1. **In the future, how likely are you to use an AI-based system if it provides you with free and personalized review materials?**  
   ☐ Very likely  ☐ Somewhat likely  ☐ Not likely  ☐ Unsure

☐ *I have read and understood the purpose of this survey, and I voluntarily agree to participate.*

**APPENDIX B: INFORMED CONSENT FORM**

|  |  |
| --- | --- |
|  | **INFORMED CONSENT** |
| **Thesis Project** | **: Optimizing NAT Readiness: A K-NN Algorithm-Driven AI System and Resource Recommendation for Grade 12 Students at STCFI** |
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**Introduction and Purpose of the Project**

This study aims to enhance the readiness of Grade 12 students of STCFI for the National Achievement Test (NAT) by developing an AI-powered system. The system utilizes the K-Nearest Neighbors (K-N) algorithm to analyze student performance and recommend appropriate learning materials. The primary goal is to personalize educational support to improve academic outcomes and NAT preparedness among students.

# Description of the Project

The project involves the design, development, and implementation of a data-driven recommendation system. Student assessment data will be collected and processed through the K-N algorithm to categorize learners based on performance and learning needs. Based on these categories, the system will suggest tailored review materials. The system will be tested in a real academic setting involving Grade 12 students of STCFI to assess its effectiveness in improving NAT readiness.

**Potential Risks and Discomforts**

There are no major risks in joining this study. Some students may feel uncomfortable being assessed. However, results will be handled respectfully and only used to support learning.

**Confidentiality**

All personal and academic information collected during the study will be treated with strict confidentiality. Data will be anonymized and stored securely. Only the researchers and authorized personnel will have access to the information. No identifiable information will be disclosed in the final report or related publications.

**Cost/Reimbursements**

There are no costs associated with participating in this study. Likewise, participants will not receive any monetary compensation. However, the educational support and personalized learning recommendations provided by the system are intended to benefit the students’ academic growth and performance in the NAT.

**Authorization**

Participants, or their legal guardians in the case of minors, will be required to sign a consent form before any data collection begins. This form outlines the purpose, procedures, risks, and rights associated with participation in the project. Authorization confirms the participant’s understanding and agreement to take part in the study.

**Voluntary Participation**

Participation in this study is entirely voluntary. Students and guardians may ask questions or request clarification about the study at any time. Declining to participate will not affect a student’s academic standing or relationship with the institution.

**Withdrawal from the Project and/or Withdrawal of Authorization**

Participants have the right to withdraw from the study at any point without any penalty or loss of benefits. If a participant chooses to withdraw, their data will be excluded from the analysis and deleted from the system if requested.

**Cost/Reimbursements**

There are no costs associated with participating in this study. Likewise, participants will not receive any monetary compensation. However, the educational support and personalized learning recommendations provided by the system are intended to benefit the students’ academic growth and performance in the NAT.

**I voluntarily agree to participate in this project.**

 **Yes**

 **No**

**Name of Participant: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_**

# Signature: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**Date: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_**