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Development of Guidance Record Management System with Exploratory Data Algorithm for Predicting Academic Performance

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Abstract: This study produces a web-based Guidance Record Management System (GRMS) designed to simplify record-keeping in guidance offices. It allows students to submit and manage their records, which counselors can access for sessions. The system also includes exploratory data analysis (EDA) features for data-driven decision-making. The admin dashboard presents visualizations and insights using EDA with Python and a Decision Tree algorithm, offering valuable information on student behavior and academic performance.

The system is built using the PHP framework Laravel, CSS and Tailwindcss for styling, JavaScript, Python's Pandas library, along with Matplotlib and Seaborn for data visualization, MySQL as the database, and Apache as the server. It is evaluated according to the ISO 25010 standard, which provides a framework for assessing software quality, ensuring that the system meets key requirements for functionality, reliability, usability, and performance.

The study successfully identified the respondents' genders as male and female. Evaluation results reveal that both male and female users, as well as technical respondents, strongly agree on the acceptability and usability of the Guidance Record Management System. Male users provided an overall average mean of 3.4, while male technical respondents rated it slightly higher at 3.5. Similarly, female users and technical respondents both rated the system with an average mean of 3.5. These results indicate a consistent positive reception across both groups, affirming the system’s effectiveness and ease of use for its intended audience.

Keywords: Web-based system, Guidance Record Management System (GRMS), Record-keeping, Exploratory Data Analysis (EDA)

I. Introduction

One of the principles of guidance counseling is to support students in their academic journey striving for academic achievements (Dhami, 2020). Aguilar-Ramat (2022) even emphasized that guidance and counseling programs itself are fundamental for ensuring a holistic educational experience and supporting students' needs.

One key responsibility of guidance counselors is to monitor the students’ both academic achievements and risk at failure. However, utilization of traditional, intuition-based approaches may not always yield optimal results.

Young and Kaffenberger (2018) articulated, "Data is vital to support optimal student achievement and social/emotional outcomes for all students. Therefore, comprehensive school counseling programs should begin and end with the continuous cycle of using data to optimize data-driven decision outcomes." Traditional, intuition-based approaches may not necessarily achieve accuracy and optimization of the data gathered by the guidance counselors.

Thus, the proponent plans to develop a web-based basic guidance record management system with built-in data analysis and visualization utilizing Exploratory Data Analysis (EDA) and Decision Tree Algorithm.

According to Gelman (2023), "Data visualization and exploratory data analysis have been recognized in recent decades as important parts of statistics and, with the development of tools to routinely produce high-quality infographics, they have become central public-facing aspects of statistics and data analytics."

By applying exploratory data analysis (EDA) to student data, guidance counselors can glean valuable insights to improve understanding of student needs, identify at-risk students, develop targeted interventions, and evaluate program effectiveness.

Building on the foundational insights from Exploratory Data Analysis (EDA), decision tree algorithms can categorize students based on various factors, enabling counselors to predict student success, tailor guidance interventions, and make data-driven decisions to maximize student potential.

IBM (2024) defines a decision tree as a non-parametric supervised learning algorithm for classification and regression tasks, featuring a hierarchical tree structure with a root node, branches, internal nodes, and leaf nodes.

The proposed web-based system will leverage Laravel's built-in security features (authentication and authorization) for a secure foundation. Laravel, a web application framework known for its expressive syntax, will provide structure and a starting point for

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development. To integrate Exploratory Data Analysis (EDA) and decision tree algorithms, Python's pandas library, an open-source, high-performance toolkit for data analysis, will be utilized.

Objectives of the Study

General Objective

The study aims to design and develop a web-based system with Exploratory Data Analysis and Decision Tree Algorithm.

Specific Objectives

To design and develop a web-based Guidance Record Management System with CRUD basic functionality;

To design and implement a core functionality within the system that establishes a secure and efficient record management system for student individual inventory;

To develop a record management system for the guidance office that empowers guidance counselors to efficiently retrieve and filter student data based on predefined criteria;

To develop an at-risk student identification system by integrating Exploratory Data Analysis and Decision Tree Algorithm within the system's report generation;

To use ISO 25010 standards behavior such as Functionality, Compatibility, Reliability, Availability and Security in the evaluation of the web-based system.

Scope and Limitations

Scope

This study focused on the design and development of a web-based system that will leverage Exploratory Data Analysis (EDA) and decision tree algorithms to facilitate the identification and support of at-risk students for the Guidance Office of Pasig City Science High School. The system aims to revolutionize student support by leveraging data-driven analysis to identify students at risk. The scope of the study encompasses the design, development, and implementation of a web-based system.

This system facilitates a secure and streamlined basic guidance record management system for administration and guidance counselors storing, managing, and analyzing student data related to the services of a guidance office. Functional requirements included the development of a secure and efficient record management system for student data. Likewise, it encompasses functionalities like data retrieval, filtering, and analysis to support at-risk student identification.

Limitations

This study focuses on developing a basic guidance record management system. This system will primarily store information relevant to guidance activities, guidance counselor responsibilities, and at-risk student identification. It is not intended as a comprehensive student data storage solution. The system's functionality is designed for guidance counselors to manage student data. While authorized administrators may have access for oversight purposes, students themselves will have limited interaction with the system beyond potentially providing some initial data upon enrollment or other specific instances. While the study aims to improve record management efficiency and at-risk student identification, it does not encompass long-term maintenance and technical support for the system beyond its initial implementation.

Theoretical Framework

The system uses a data-driven approach to identify students at risk of academic difficulties. This framework is grounded in three key areas:

Data-Driven Decision Making in Education

The American School Counselor Association, one of the proponents of data-driven decision making (DDDM), has published multiple papers analyzing student data. Educators can gain insights into student performance, identify trends, and tailor interventions to individual needs. This approach offers several benefits that include: gaining valuable insights into student performance, instructional strategies, resource allocation, and overall school effectiveness (Fernandes, 2023).

This is supported by the systems theory which views an organization (e.g., a school) as a complex system of interconnected parts. It emphasizes that data and feedback loops are critical for making informed decisions to optimize system performance. Wilkinson, L.A. (2011)

Exploratory Data Analysis (EDA) for Educational Research

Exploratory Data Analysis (EDA) is a critical first step in data analysis. This process involves exploring, summarizing, and visualizing student data to discover patterns, trends, and relationships. EDA helps researchers gain a deeper understanding of the data before applying more complex statistical methods (IBM, 2024).

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This concept is supported by the constructivist theory which emphasizes that knowledge is constructed through exploration, observation, and interpretation of data. Hein, G. E. (1991, October)

Decision Tree Algorithms for Student Classification

Decision tree algorithms are a type of machine learning technique used for classification tasks. These algorithms create a tree-like structure that classifies data points based on a series of sequential decisions.

This concept is supported by decision theory which focuses on the principles and frameworks used to make optimal decisions, often based on probabilistic or statistical models.

Conceptual Framework

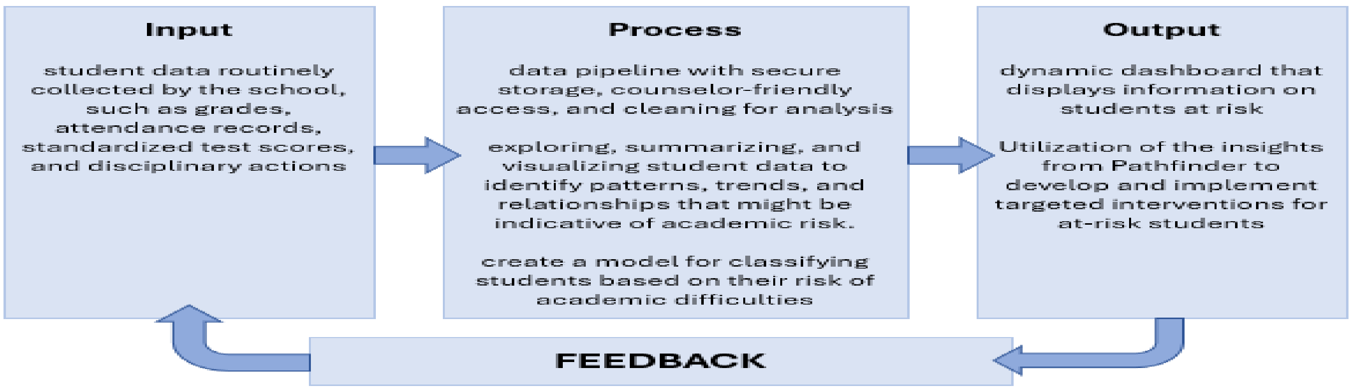

Figure 1: The Conceptual Framework

This figure presents the process of the system, which is as follows:

As input, the data sources are taken from the student data routinely collected by the school, such as grades, attendance records, standardized test scores, and disciplinary actions.

The system, which also offers a basic guidance record management system, established a secure and efficient record management system for student data that enabled: (a) secure data storage and access control, (b) efficient data entry, retrieval, and filtering functionalities for counselors, (c) data cleaning and pre-processing for analysis. Through Exploratory Data Analysis (EDA) and a decision tree algorithm, student data explored, visualized, and modeled to identify factors associated with academic risk.

By analyzing student data, the system generates a dynamic risk dashboard to identify students needing additional support, enabling counselors to tailor interventions. And by leveraging data analysis (EDA and decision tree), the system generates a dynamic risk dashboard that pinpoints students at risk of academic difficulties. This empowers counselors to tailor interventions and support for these students based on their specific needs.

Synthesis

The integration of Artificial Intelligence (AI) into the Philippine educational system presents promising opportunities for enhancing the learning experience of students, as highlighted by Estrellado (2023). However, effective integration requires a robust, technology-based record-keeping system. According to UP Mindanao's handbook (2019), an efficient record-keeping system necessitates a well-structured file classification plan. For institutions like Pasig City Science High School (PCSHS), implementing a foundational guidance record management system is a critical first step. Lopez and Lorejo (2023) emphasize that readily accessible, reliable information supports informed decision-making.

If PCSHS establishes a digitalized record-keeping system, machine learning algorithms, such as the Decision Tree Algorithm, can be applied to support data-driven interventions. For example, Sonza and Tumibay (2020) demonstrated how this algorithm could identify specific interventions in promoting gender equality. The proposed system will incorporate Python programming for analytics, leveraging libraries like pandas and seaborn to analyze correlations between various student attributes and performance metrics (Flores, 2023). This aligns with the findings of Parreño (2023), who underscored the importance of actionable interventions for at-risk students.

Local educational institutions have also explored data-driven approaches. Bernardo et al. (2021, 2022) used machine learning to identify factors affecting English proficiency and low math performance, respectively, highlighting the value of addressing interconnected issues. Similarly, Apolinar-Gotardo (2019) applied Data-Driven Decision Making (DDDM) to predict students at risk of academic failure, advocating proactive educator interventions. Studies like those by de Jesus and Ledda (2021), which utilized Fuzzy Logic-Based prescriptive analytics, further emphasize the growing relevance of data-driven methodologies in addressing dropout rates.

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Internationally, decision tree algorithms have been effectively utilized for student classification and risk assessment. For instance, Muraina, Aiyegbusi, and Abam (2023) demonstrated their efficiency in predicting academic performance, while Stanley, Petscher, and Pentimonti (2019) highlighted their role in universal screening for academic struggles. Exploratory Data Analysis (EDA), combined with machine learning, has proven essential in deriving actionable insights. Osborne and Lang (2023) demonstrated the efficacy of neural network models in identifying at-risk students, while studies by Muliani and Sihombing (2024) showcased how EDA aids in predicting timely graduations.

For PCSHS, adopting such approaches aligns with best practices in modern education. By combining decision tree algorithms, Python-based EDA, and insights from both local and international studies, the proposed system aims to empower educators with data-driven tools to foster student success.

II. Methodology

Research Design

The study's research design encompasses both descriptive and developmental approaches. The descriptive study gathers information regarding the current procedures and challenges guidance counselors face in handling student data. The developmental phase focuses on the design, development, and implementation of the system—a web-based guidance record management system with data analysis and visualization capabilities.

Data Collection Method

The proponent's main data sources include interviews and surveys conducted with representatives from Pasig City Science High School's Guidance Office. These primary data sources provide firsthand insights into the procedures, challenges, and requirements of the guidance counselors. Secondary sources consist of previous school years' student records, existing document formats handled by the Guidance Office, and relevant studies and literature cited in the literature review. These sources help in understanding the context and background, as well as in shaping the development of the system.

System Development Life Cycle

The proponent utilizes the System Development Life Cycle (SDLC) as the approach to the development phase of the project. The SDLC focuses on systematic planning, development, and implementation, leading to the successful completion of the system.

Waterfall Methodology:

The Waterfall methodology consists of the following iterative phases: analysis, design, implementation, testing, and operation. In the Waterfall model, the stages of the development process are organized sequentially, resembling a cascade. Each phase ends with an intermediate outcome (milestone) such as a requirements specification document, a defined software architecture, or an application in the alpha or beta stage.

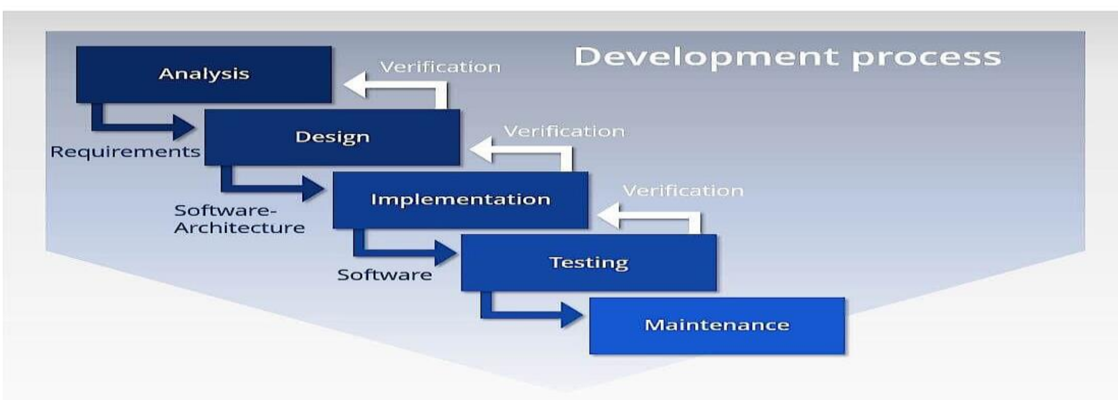

Figure 2. The Waterfall Methodology

This figure presents the methodology used for the design and development of the system.

Analysis: This phase involves understanding how the Guidance Office works, discussing project requirements, and identifying the features needed for the system. The focus is on at-risk student identification and the digitization of the Guidance Office's tasks and responsibilities.

Design: This phase includes creating detailed design specifications, including database design and system architecture for the system.

Implementation: This phase involves programming and coding based on the established design, bringing the system to life.

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Testing: In this phase, the system undergoes integration and comprehensive testing of system components to ensure functionality and reliability.

Maintenance: This phase addresses any issues that arise during the project's timeline and ensures the system remains functional and up-to-date.

Database Design

Database Design focuses on the efficient management and retrieval of student data. A well-designed database ensures data security, performance, and integrity, crucial for supporting the system's objectives of identifying at-risk students and streamlining guidance office operations.

Context Diagram

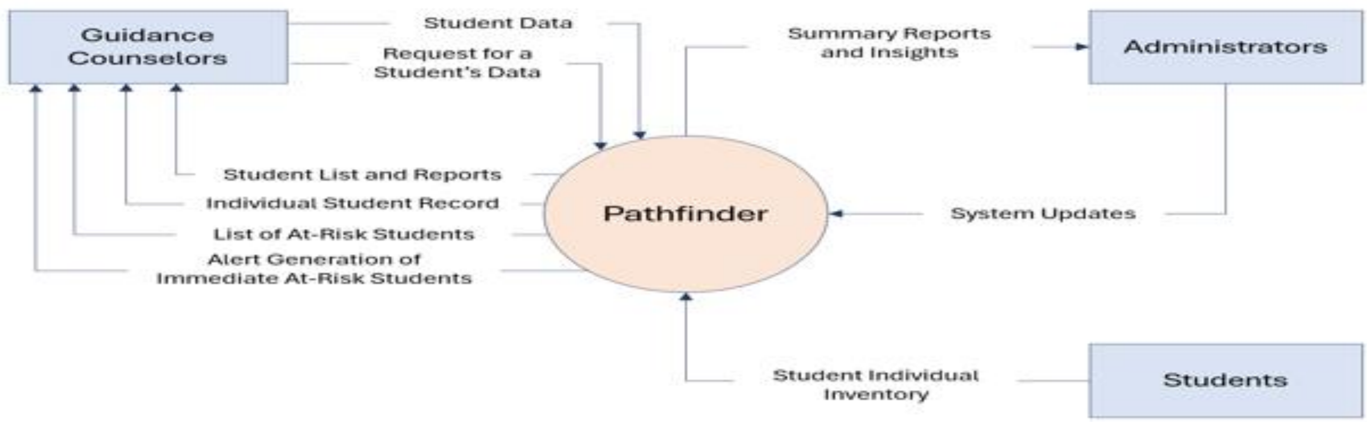

Figure 3. The Context Diagram

This figure presents the context diagram for the system depicts its interaction with users (guidance counselors and administrators) and the system. This figure highlights key data flows such as student information input, data analysis, and report generation.

Development Tools

The following tools are used in coding, testing, version control, and deployment, summarizing the developmental environment of the system:

Development Environment: Laravel (PHP framework), Python (for data analysis).

Database: MySQL.

Full-stack: Livewire

Coding Environment: Visual Studio Code

Respondents of the Study

The study involves two respondent groups: (a) users and (b) technical experts. User respondents are chosen based on their experiences in navigating systems in their work, while those with backgrounds in information technology, managing system, or exposure to system development are the technical respondents. There are 60 respondents in the user group and 40 in the technical group, making a total of 100 respondents representing both male and female genders.

The study employed a simple random sampling technique to select the sample. Slovin’s Formula is used to get the number of samples

Respondents Distribution

Table 1. Respondents of the Study

Respondents	No. of Respondents	Percentage
Users	60	60%
Technical	40	40%
Total	**100**	**100%**

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Statistical Tools

The statistical tools utilized in this study are the frequency percentage and weighted mean.

- Frequency Percentage

This method is employed to ascertain the relative distribution of respondents, indicating the percentage of observations based on their gender.

- Weighted Mean

The weighted arithmetic mean is employed to establish the central tendency of a set of observations when each quantitative measurement does not carry equal significance.

Likert Scale

The 4-point Likert scale is employed to analyze and interpret the data collected from respondents, utilizing weighted points and scales for measurement.

Table 3. Four-Point Likert's Scale

Weighted Point	Scale	Difference	Verbal Interpretation
4	4.00 – 3.00	1.00	Strongly Agree
3	2.99 – 2.00	0.99	Agree
2	1.99 – 1.00	0.99	Disagree
1	1.00 – 0.99	0.01	Strongly Disagree

III. Discussion of Results

Project Description

The output of the study is a web-based Guidance Record Management System. The Guidance Record Management System is designed to streamline the record-keeping processes of the guidance office by providing students with a platform to submit and manage their individual inventory records. Additionally, the system integrates exploratory data analysis features, allowing for data-driven decision-making. The admin dashboard offers visualizations and insights using exploratory data analysis (EDA) by Python and a Decision Tree algorithm, providing valuable information on student behavior and academic performance in relation to the guidance office.

The system is built using the PHP framework Laravel, CSS and Tailwindcss for styling, JavaScript, Python's Pandas library, along with Matplotlib and Seaborn for data visualization, MySQL as the database, and Apache as the server. It is evaluated according to the ISO 25010 standard, which provides a framework for assessing software quality, ensuring that the system meets key requirements for functionality, reliability, usability, and performance.

Project Evaluation Results

The system is evaluated through two methods: (a) assessments by user respondents and (b) assessments by technical respondents. The user group's evaluation centered on the system's acceptability and usability based on their experiences, while the technical group focused on its technical quality and performance. Both evaluations were conducted using the ISO 25010 standards.

Shown below is the comparison table of Users and Technical Respondents.

Table 4: Comparison of Evaluations of User and Technical-Respondents

Criteria	Respondents (100)							
	Users (60)				Technical Personnel (40)			
	Male (41)		Female (19)		Male (23)		Female (17)	
	WM	VI	WM	VI	WM	VI	WM	VI
2. Functional Suitability	3.4	SA	3.5	SA	3.6	SA	3.5	SA
2. Compatibility	3.5	SA	3.5	SA	3.5	SA	3.5	SA
3. Reliability	3.4	SA	3.5	SA	3.5	SA	3.6	SA
4. Availability	3.5	SA	3.5	SA	3.6	SA	3.5	SA
5. Security	3.4	SA	3.5	SA	3.6	SA	3.5	SA
Overall Average Mean (Gender)	**3.4**	**SA**	**3.5**	**SA**	**3.5**	**SA**	**3.5**	**SA**

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Table 4 shows the comparison of evaluations of User and Technical-Respondents. Male users' overall average mean is 3.4 interpreted as "Strongly Agree" while male technical respondents' overall average mean is 3.5 interpreted as "Strongly Agree". Female users' overall average mean is 3.5 interpreted as "Strongly Agree" while female technical respondents' overall average mean is also 3.5 interpreted as "Strongly Agree". All respondents (users and technical) strongly agreed on the acceptability and usage of the application.

IV. Conclusion

The study successfully identified the respondents' genders as male and female. Evaluation results reveal that both male and female users, as well as technical respondents, strongly agree on the acceptability and usability of the Guidance Record Management System. Male users provided an overall average mean of 3.4, while male technical respondents rated it slightly higher at 3.5. Similarly, female users and technical respondents both rated the system with an average mean of 3.5. These results indicate a consistent positive reception across both groups, affirming the system's effectiveness and ease of use for its intended audience.

Recommendations

Given the limitations of this study, future researchers are encouraged to expand the scope of the Guidance Record Management System to serve as a more comprehensive student data management tool. This could include integrating additional functionalities such as long-term student tracking, academic performance monitoring, and enhanced communication features between counselors, students, and parents. To address the limitation regarding limited student interaction, future developments could allow students to engage more actively with the system by accessing their records, tracking progress, and requesting guidance sessions.

Furthermore, implementing long-term maintenance and technical support mechanisms would ensure the system's sustainability beyond initial deployment. This may include automatic updates, security patches, and user support to keep the system running efficiently. Exploring the integration of data analytics could also help in identifying patterns in student behavior, further supporting at-risk student identification and personalized interventions.

References

1. Aguilar-Ramat, G. (2022). Extent of implementation of the guidance program in the public schools of Urdaneta City. IJAMS-JULY-ISSUE-275-301. https://www.ijams-bbp.net/wp-content/uploads/2022/08/IJAMS-JULY-ISSUE-275-301.pdf
2. American School Counselor Association. (2024, June). School counselor. https://schoolcounselor.org/
3. American Statistical Association (ASA). (2023, January 2). JEDI corner: From visualization to 'sensification'. Amstat News. https://magazine.amstat.org/blog/2021/10/01/jedi-corner-october-2021/
4. Apolinar-Gotardo, M. (2019). Using decision tree algorithm to predict student performance. https://doi.org/10.29322/IJSRP.13.04.2023.p13704
5. Bai, N. (2023). Philippine Statistics Authority (PSA). Educational challenges in the Philippines. https://pids.gov.ph/details/news/in-the-news/educational-challenges-in-the-philippines
6. Beloy, R. G. (2024). Because every learner matters: A journey on saving one learner at a time through intervention projects. Parañaque National High School-Main. https://pnhsmain.depedparanaquecity.com/uncategorized/intervention-projects/
7. Bernardo, A. B. I., Cordel, M. O. II, Lapinid, M. R. C., Teves, J. M. M., Yap, S. A., & Chua, U. C. (2022). Contrasting profiles of low-performing mathematics students in public and private schools in the Philippines: Insights from machine learning. Journal of Intelligence, 10(3), 61. https://doi.org/10.3390/jintelligence10030061
8. Bernardo, A. B. I., Cordel, M. O. II, Lucas, R. I. G., Teves, J. M. M., Yap, S. A., & Chua, U. C. (2021). Using machine learning approaches to explore non-cognitive variables influencing reading proficiency in English among Filipino learners. Education Sciences, 11(10), 628. https://doi.org/10.3390/educsci11100628
9. Cindy, G. de, Jesus, M. K. C., & Ledda, M. K. C. (2021). Intervention support program for students at risk of dropping out using fuzzy logic-based prescriptive analytics. 144-149. https://doi.org/10.1109/CSPA52141.2021.9377304
10. Courtney, M. B. (2021). Exploratory data analysis in schools: A logic model to guide implementation. International Journal of Education Policy & Leadership, 17(4). https://doi.org/10.22230/ijepl.2021v17n4a1041
11. Damie, L., Jayson, K. P., Julian, R., Ralph, M. P., Caparas, G. L. D., & Intal, G. L. D. (2019). MyCounselor: Guidance and counseling support system for higher education institute in the Philippines. https://doi.org/10.1145/3374549.3374578
12. DataHeadhunters. (2022, February 20). How to use Python for data-driven decision making in education. https://www.dataheadhunters.com/how-to-use-python-for-data-driven-decision-making-in-education/
13. Dhami, M. (2020, December 28). The importance of guidance and counselling in adolescents' life. Times of India. https://timesofindia.indiatimes.com/readersblog/manisha-dhami/the-importance-of-guidance-and-counselling-in-adolescents-life-28624/

14. Estrellado, C. J. (2023). Artificial intelligence in the Philippine educational context: Circumspection and future inquiries. International Journal of Scientific Research and Publications, 13(4), 16-23. https://doi.org/10.29322/IJSRP.13.04.2023.p13704
15. Fernandes, J. (2023). The role of data-driven decision-making in effective educational leadership. ABAC Journal, 27(Special Issue 2).
16. Flores, I. M. (2023, May 12). Philippine student employability correlation heatmap (Python: pandas & seaborn). Medium. https://www.geeksforgeeks.org/how-to-create-a-seaborn-correlation-heatmap-in-python/
17. Hein, G. E. (1991, October). Constructivist learning theory: The museum and the needs of people. CECA (International Committee of Museum Educators) Conference, Jerusalem, Israel. Lesley College, Massachusetts, USA.
18. IBM. (2024, June). Exploratory data analysis. https://www.ibm.com/docs/en/fci/6.6.0?topic=developing-exploratory-data-analysis
19. IBM. (n.d.). Definition of decision tree. IBM. https://www.ibm.com/topics/decision-trees
20. Leeway Hertz. (2024). AI use cases & applications across major industries. https://www.leewayhertz.com/leewayhertz-next-gen-generative-ai-development-services-transform-global-businesses/
21. Laravel Documentation. (n.d.). https://laravel.com/docs/11.x/installation
22. Maphosa, M. W., Doorsamy, W., & Paul, B. S. (2023). Student performance patterns in engineering at the University of Johannesburg: An exploratory data analysis. IEEE Access, 11, 48977-48987. https://doi.org/10.1109/ACCESS.2023.3277225
23. Masters in Data Science. (2024). What is a decision tree? Retrieved June 29, 2024, from https://www.mastersindatascience.org/learning/machine-learning-algorithms/decision-tree/
24. Matthew B. Courtney. (2021). Exploratory data analysis in schools: A logic model to guide implementation. International Journal of Education Policy & Leadership, 17(4). https://doi.org/10.22230/ijepl.2021v17n4a1041
25. Mienye, I. D., Sun, Y., & Wang, Z. (2019). Prediction performance of improved decision tree-based algorithms: A review. Procedia Manufacturing, 35, 698-703. https://doi.org/10.1016/j.promfg.2019.06.011
26. Muliani, S., & Sihombing, V. (2024). Implementation of exploratory data analysis and artificial neural networks to predict student graduation on-time. Sinkron, 8(2), 1188-1199. https://doi.org/10.33395/sinkron.v8i2.13658
27. Muraina, I., Aiyegbusi, E., & Abam, S. (2023). Decision tree algorithm use in predicting students' academic performance in advanced programming course. International Journal of Higher Education Pedagogies, 3, 13-23. https://doi.org/10.33422/ijhep.v3i4.274
28. Osborne, J. B., & Lang, A. (2023). Predictive identification of at-risk students: Using learning management system data. Journal of Postsecondary Student Success, 2, 108–126. https://doi.org/10.33009/fsop_jpss132082
29. Parreño, S. J. (2023). School dropouts in the Philippines: Causes, changes, and statistics. Sapienza: International Journal of Interdisciplinary Studies, 4(1), e-23002. https://doi.org/10.51798/sijis.v4i1.552
30. Patacsil, F. F., Dina, P., & Roaring, B. (2023). Analyzing flexible learning implementation using decision tree approach. Journal of Educational Science and Technology. https://doi.org/10.26858/est.v9i2.36677
31. Sonza, R., & Tumibay, G. (2020). Decision tree algorithm in identifying specific interventions for gender and development issues. Journal of Computer and Communications, 8, 17-26. https://doi.org/10.4236/jcc.2020.82002
32. Stanley, C., Petscher, Y., & Pentimonti, J. (2019). Classification accuracy. Washington, DC: U.S. Department of Education, Office of Elementary and Secondary Education, Office of Special Education Programs, National Center on Improving Literacy. Retrieved from https://improvingliteracy.org
33. Steele, Katie and H. Orri Stefánsson, "Decision Theory", The Stanford Encyclopedia of Philosophy (Winter 2020 Edition), Edward N. Zalta (ed.), URL = <https://plato.stanford.edu/archives/win2020/entries/decision-theory/>.
34. University of the Philippines Mindanao. (2019). Complete handbook on FCG and RRDS. https://www2.upmin.edu.ph/images/2020/Student%20Handbook%20-%20pages%20.pdf
35. Vivek, V., Patil, D. S., Patil, S., & Tayade, S. (2023). Student record management system using Django. International Journal for Science Technology and Engineering, 11(5), 18-23. https://doi.org/10.22214/ijraset.2023.51366
36. Wilkinson, L.A. (2011). Systems Theory. In: Goldstein, S., Naglieri, J.A. (eds) Encyclopedia of Child Behavior and Development. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-79061-9_941
37. Young, A., & Kaffenberger, C. (2018, September). Data as easy as 1-2-3. School Counselor. https://www.schoolcounselor.org/Newsletters/October-2018/Data-as-Easy-as-1-2-3?st=NJ