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IntelliSIS: Perception on the Design and Implementation of an Intelligent Student Information System

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Abstract

Student Information System (SIS) is significant to modern educational institutions, providing a centralized platform for student-related data handling and management. Traditional SIS often lacks the advanced capabilities to analyze data and predict student performance or academic success. This paper aimed to design and implement an SIS that integrates a machine learning model using Logistic Regression to provide predictive analytics on student performance or academic success in Mandaue City College (MCC) situated in Mandaue City, Cebu. A survey was conducted to the institution's stakeholders, including office personnel, faculty, and students to assess current workflows, identify pain points, and their perception towards implementing an intelligent SIS highlighting its potential to transform student information management. The system development methodology will utilize the structured Waterfall Model. The findings showed that the proposed system should be further pursued which can significantly provide data-driven insights for improving the academic and operational aspects of the institution in providing better services to the students anchored towards the Strategy Map 2027 of the Mandaue City Government. Thus, the implementation of the intelligent SIS demonstrates its potential as a technological model for other local higher education institutions.

Keywords: Student Information System, Machine Learning, Academic Performance, Predictive Analytics, IntelliSIS

Introduction

In the rapidly evolving landscape of education, the effective management and utilization of student information have become increasingly critical. Student Information Systems (SIS) play a vital role in educational institutions by facilitating the efficient handling of student-related data, supporting administrative operations, and enhancing institutional decision-making processes (Murugan, 2020). However, traditional SIS platforms often fall short in addressing the dynamic and data-driven needs of modern academic institutions, particularly in their limited capacity to analyze large datasets and predict student outcomes effectively.

The prediction of student performance and academic success has garnered significant attention in educational research due to its potential to enable early interventions and provide targeted student support (Ahmed, 2024). To address this gap, the researchers propose IntelliSIS—an Intelligent Student Information System specifically designed to enhance data utilization in educational settings. This system integrates machine learning algorithms and predictive analytics to significantly improve educational service delivery. IntelliSIS is envisioned to assist administrators, faculty, and students at Mandaue City College (MCC) by providing actionable, data-driven insights that facilitate informed decision-making and lead to improved academic outcomes.

The primary objective of IntelliSIS is to transform the management of student data through the integration of advanced technologies, particularly machine learning. By employing sophisticated algorithms, the system delivers predictive analytics capable of identifying academically at-risk students and forecasting academic performance with accuracy. These insights empower educators to implement timely and personalized interventions, grounded in data-informed strategies (Ojajuni et al., 2021). Additionally, IntelliSIS functions as a centralized platform for managing student information, thereby enhancing data accuracy, accessibility, and security. Through secure and systematic data management, the system supports more effective academic planning and decision-making processes.

As SIS continues to optimize student services workflows (Al-Hunaiyyan et al., 2021), this study explores the design and implementation of IntelliSIS, with a focus on its potential to improve student information management within the institution. It addresses key challenges such as data fragmentation, time-consuming manual processes, and the lack of predictive insights for identifying academically struggling students. By mitigating these issues, IntelliSIS offers an innovative solution that enhances the efficiency, accuracy, and effectiveness of educational administration—aligning with the institutional development roadmap of MCC and the broader Strategy Map 2027 of the Mandaue City Government.

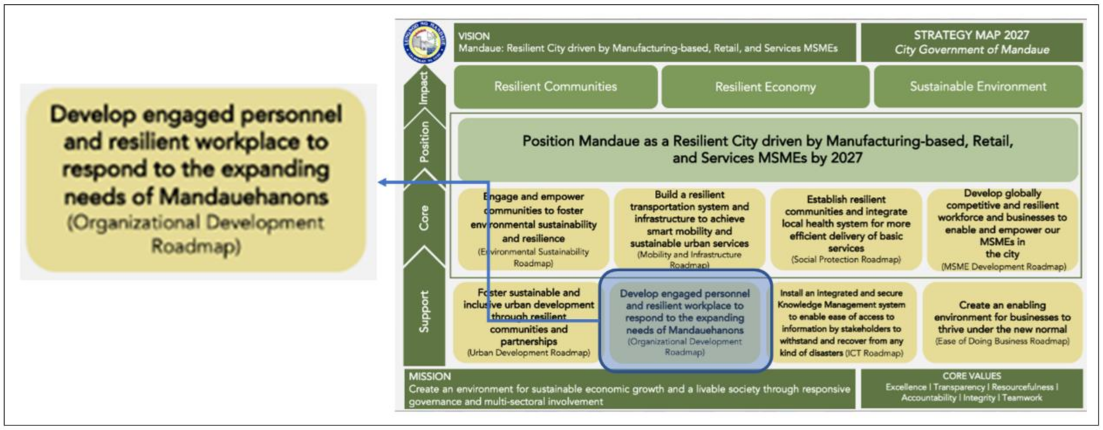

Figure 1: Mandaue City Strategy Map 2027

The Strategy Map 2027 was developed through a collaborative effort among various city offices and department heads under the Performance Governance System (PGS), spearheaded by the Office of Strategy Management (OSM) (Office of Strategy Management – Mandaue City, n.d.). Rooted in a strategic governance framework, this approach supports the educational institution's mission to promote data-driven decision-making and to continually enhance both academic and operational services for the students of Mandaue City.

Literature Review

The integration of machine learning (ML) and data analytics has significantly transformed the capabilities of Student Information Systems (SIS), enhancing their functions to include the prediction of student performance and academic outcomes. These advancements enable educational institutions to make informed, data-driven decisions, ultimately improving educational service delivery and student support systems. This section reviews relevant literature on the application of machine learning and data analytics in student performance prediction across diverse educational settings.

Ahmed (2024) conducted a comparative analysis of multiple machine learning algorithms to predict student performance in higher education, emphasizing the importance of model refinement and rigorous data preprocessing. While the study demonstrated promising results, it recommended the use of larger, more diverse datasets, longitudinal data analysis, and enhanced model interpretability.

Yağcı (2022) investigated the use of ML algorithms to predict final exam scores based on midterm performance among 1,854 undergraduate students in Turkey. The study evaluated several algorithms including Random Forests, Neural Networks, Support Vector Machines (SVM), Logistic Regression, Naïve Bayes, and k-Nearest Neighbors. Although the models achieved high accuracy, the study recommended incorporating behavioral, demographic, and socio-economic predictors to further improve prediction performance.

Tao-Hongli (2024) proposed a novel feature selection method called Adaptive Sea Horse Optimization (ASHO), applied to the xAPI-Edu-Data dataset. The study employed Z-score normalization for preprocessing and the XGBoost algorithm for prediction, using a dataset of 480 students categorized by societal, academic, and behavioral attributes. Results showed improved performance over traditional methods, but the study highlighted the need for model validation using multiple datasets.

Ahajjam, Moutaib, Aissa, Azrour, Farhaoui, and Fattah (2022) explored the use of Artificial Neural Networks (ANNs) to predict student academic performance in Morocco. Using a dataset of over 142,000 student records, the study highlighted the importance of clean data and emphasized the role of effective school guidance. It recommended the inclusion of additional features such as attendance, engagement, socio-economic background, and demographic data.

Nabil, Seyam, and Abou-Elfetouh (2021) utilized Deep Neural Networks (DNNs) to predict performance in challenging courses such as Programming and Data Structures. Using the xAPI-Edu-Data dataset, the study emphasized the value of early prediction to reduce dropout rates and suggested the incorporation of additional datasets to further improve model accuracy.

Yousafzai, Afzal, Imran, Ali, and Khan (2021) developed a hybrid DNN model using an attention-based Bidirectional Long Short-Term Memory (BiLSTM) network for student performance prediction. The authors stressed the role of Educational Data Mining (EDM) and recommended future studies incorporate socio-cultural and behavioral data, as well as longitudinal datasets, to enhance model effectiveness.

Essayad and Abdellah (2024) applied various ML techniques—including decision trees, logistic regression, SVMs, and neural networks—to forecast baccalaureate outcomes in Morocco. Their findings indicated the value of both classification and regression approaches, but they advised the inclusion of socio-economic and health-related variables to enhance prediction accuracy.

Bhushan, Verma, Garg, and Negi (2024) focused on predicting Semester Grade Point Averages (SGPA) using various ML algorithms. The study emphasized the importance of high-quality data and continuous monitoring, and recommended adding more attributes and developing an application to enable stakeholders to evaluate student performance in real time.

Hussain, Akbar, Hassan, Aziz, and Urooj (2024) explored EDM approaches to predict academic outcomes and called for the use of publicly available large datasets. The study emphasized the value of simplified neural network models and the importance of comprehensive feature sets for more accurate prediction.

Junejo, Shaikh, and Larik (2024) introduced the Students' Academic Performance Prediction Network (SAPPNet), a deep learning model developed during the COVID-19 pandemic. Using data from Jordan University, SAPPNet outperformed traditional models, although the authors recommended improving its interpretability, scalability, and computational efficiency.

Muraina, Aiyegbusi, and Abam (2023) employed the Chi-squared Automatic Interaction Detector (CHAID) decision tree algorithm to predict performance in advanced programming courses. The study emphasized the role of academic performance in future success and recommended more comprehensive datasets for improved prediction.

Umamaheswari, Vanitha, Devi, Thephoral, and Basha (2024) analyzed data from Learning Management Systems (LMS) and social media platforms using a modified SVM approach. While the approach outperformed traditional methods, the authors suggested applying the model to broader populations and integrating additional relevant data.

Vimarsha, Prakash, Krinkin, and Shichkina (2024) implemented a Co-Evolutionary Hybrid Intelligence (CHI) model for predicting academic performance. Their research highlighted the importance of transparency and accountability in educational decision-making, recommending validation of the model in varied academic contexts.

Dervenis, Stoufis, Kyriatzis, and Fitsilis (2022) analyzed ML applications in mathematics education, developing models to classify student performance levels. While the results were promising, the study stressed the need for longitudinal data and broader data sources to enhance model reliability and accuracy.

Lastly, Guanin-Fajardo, Guaña-Moya, and Casillas (2024) emphasized forecasting academic success and identifying dropout risks using ML techniques. The study advocated for the inclusion of additional variables to ensure consistent measurement and proposed that insights gained from the models could inform classroom management strategies and improve educational outcomes.

Methodology

The proponent of this paper on the Design and Implementation of an Intelligent Student Information System (IntelliSIS) utilized the Waterfall Model, which is a structured software development methodology.

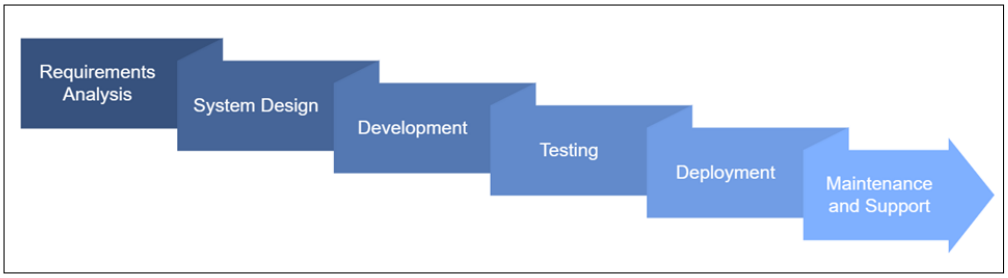

Figure 2: Waterfall Model

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As illustrated in Figure 2, the software development process follows a linear or sequential model, commonly known as the Waterfall model, in which each phase progresses in a structured and rigid manner, although some degree of overlap and feedback between phases is occasionally permissible (ScienceDirect, n.d.). This section outlines the procedures undertaken in the ongoing design and implementation of the system.

Requirements Analysis

In this phase, a survey was conducted to the students and selected student service office personnel in Mandaue City College (MCC) which was selected as the primary research environment. The survey tool for this study has a 20-item questions with a four-point Likert Scale to evaluate the perceptions on the current status and challenges of handling and managing student information, on the usefulness and impact of IntelliSIS, on the capabilities and functionalities of IntelliSIS, on the various factors affecting student performance or academic success, and on the challenges with the implementation and utilization of IntelliSIS. The respondents were asked to answer the questionnaire distributed through Google Forms. Descriptive statistics are used to present the answers of the respondents.

Table 1: Respondents Grouped by Institution Role

Role	Frequency	Percentage
Students	86	92.5%
School Personnel	7	7.5%
TOTAL	93	100%

System Design

In this phase, the system architecture, data model, machine learning model development process and design of IntelliSIS were initially created. The system adhered to the client-server architecture that defines the client and server components. As shown in Figure 3, the client component is responsible for requesting the needed resources from the server. The server component is responsible for processing the requests and delivering the services to the client.

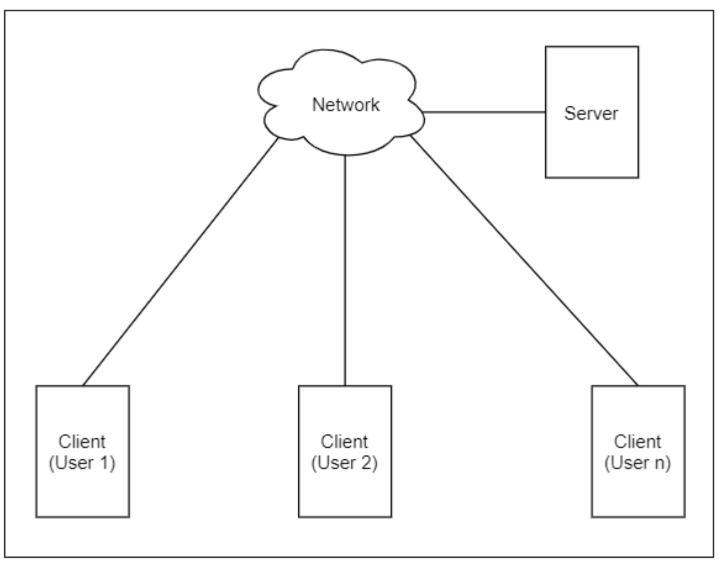

Figure 3: Client-Server Architecture

The system design includes the development of user interface (UI) prototypes to visualize the structure and functionality of the application. Figma, a collaborative interface design tool, was utilized for creating the UI layouts and interactive prototypes (Figma, n.d.). The initial prototypes developed during the design phase are presented in the figures below.

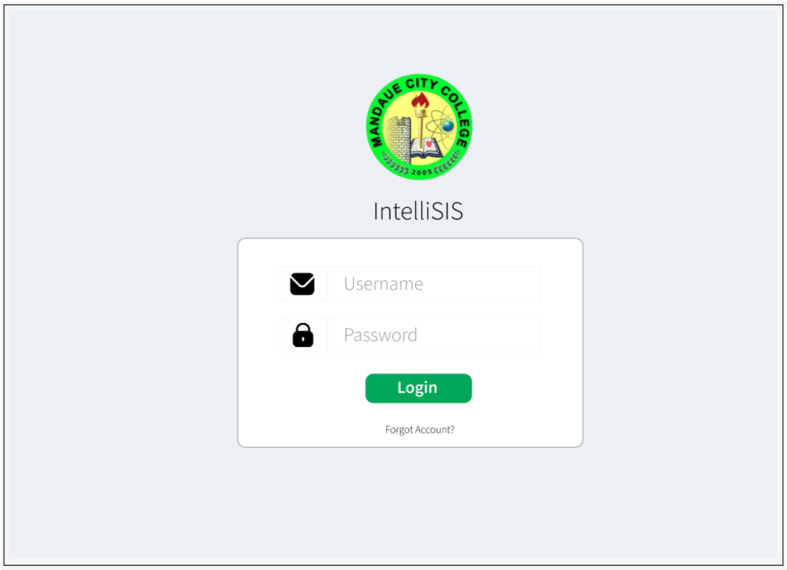

Figure 4: Login Screen

The figure above shows the login screen design which serves as the gateway or entry point of the system. The user will be required to input the credentials which will be validated by the system. Only those authorized users will be given access to the system.

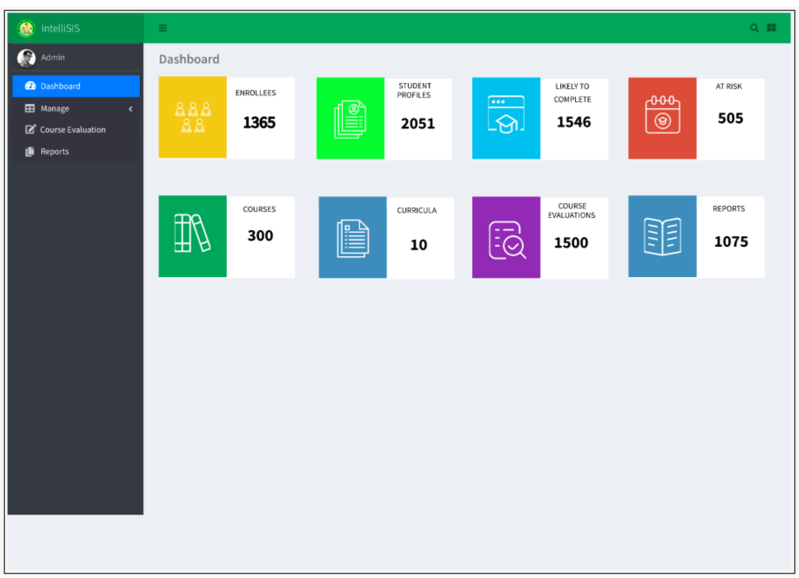

Figure 5: Dashboard Screen

The figure above shows the dashboard screen design which displays the visual data of the system. The screen will be used to monitor and convey student-related information and may display data in other visual formats.

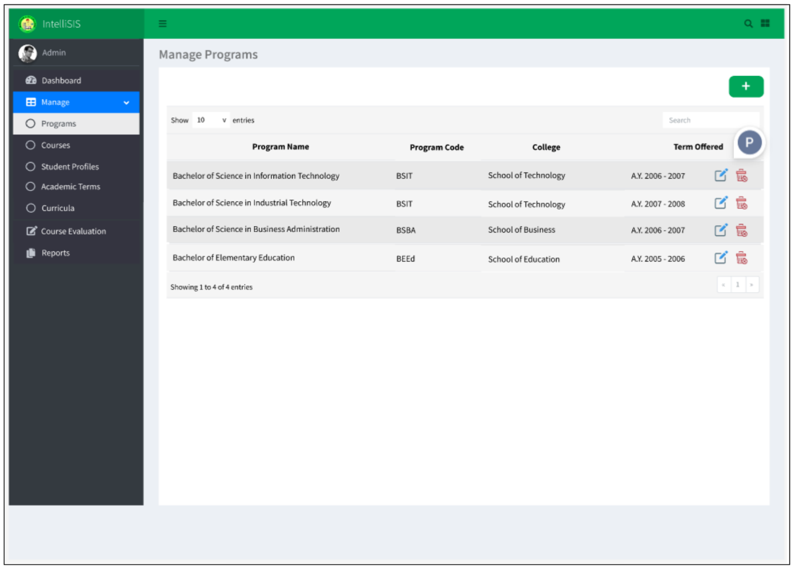

Figure 6: Manage Programs Screen

The figure above shows the manage programs screen design which displays the management of programs offered in MCC. The screen will be used to add, edit, view and deactivate program records.

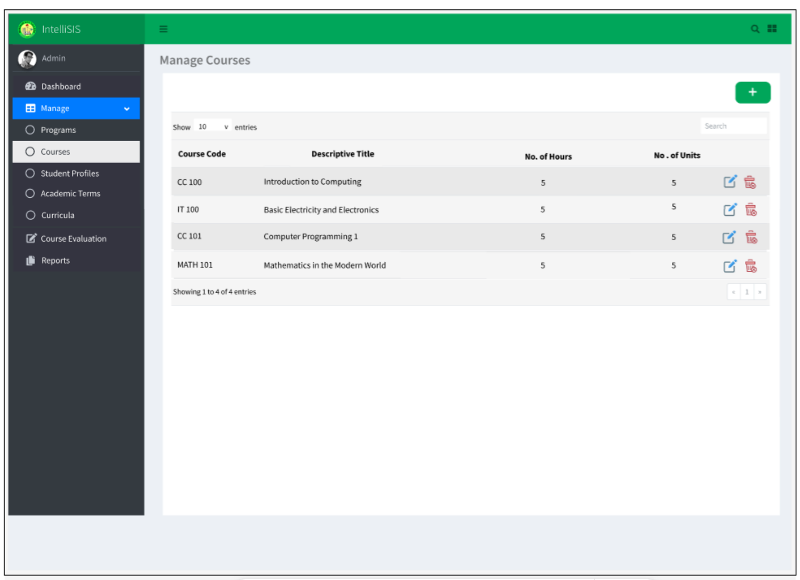

Figure 7: Manage Courses Screen

The figure above shows the manage courses screen design which displays the management of courses offered in MCC for a particular program. The screen will be used to add, edit, view and deactivate course records.

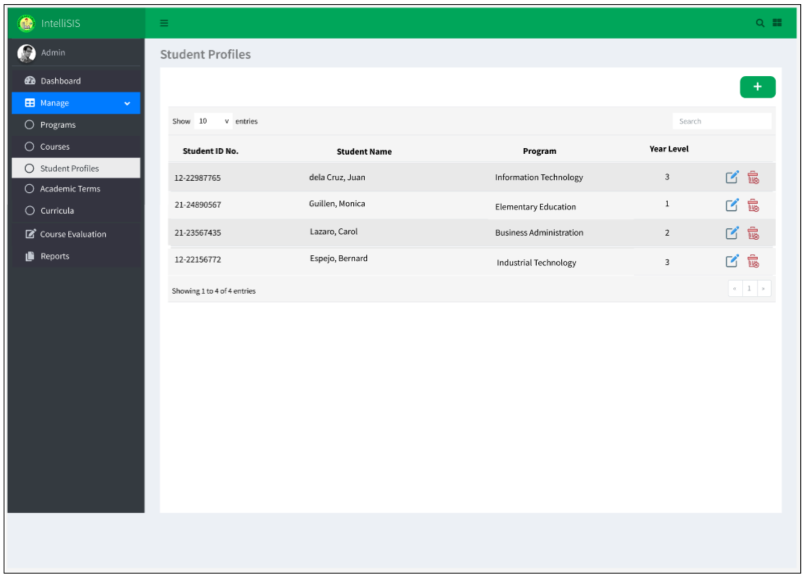

Figure 8: Manage Student Profiles Screen

The figure above shows the manage student profiles screen which displays the management of student profile records in MCC. The screen will be used to add, edit, view and deactivate student profile records.

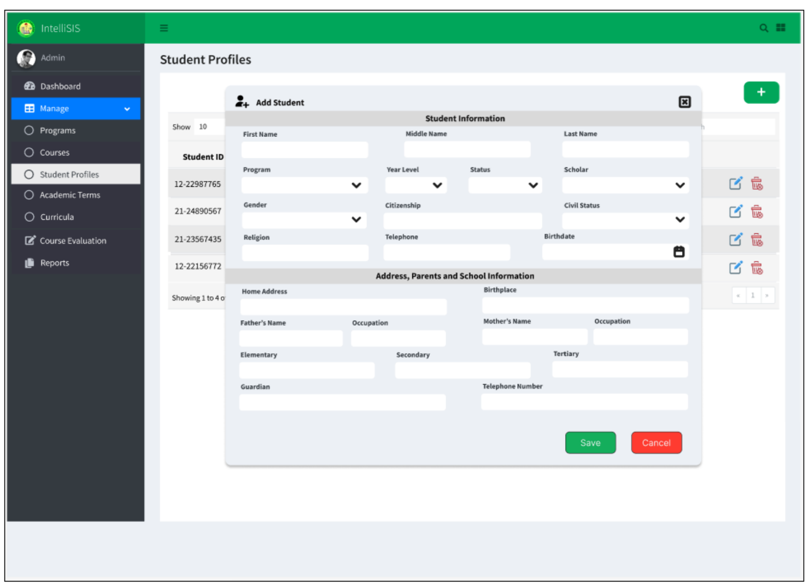

Figure 9: Add Student Profile Screen

The figure above shows the add student profile screen design which displays the needed inputs for student-related information. The user will be required to specify details for a particular profile of a student to add.

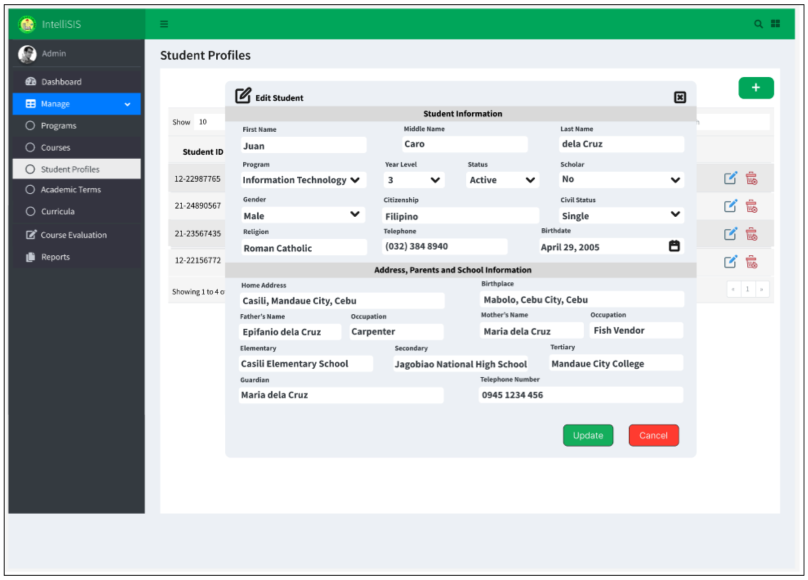

Figure 10: Edit Student Profile Screen

The figure above shows the edit student profile screen design which displays the stored student-related information. The user will be required to specify details for a particular profile of a student to update.

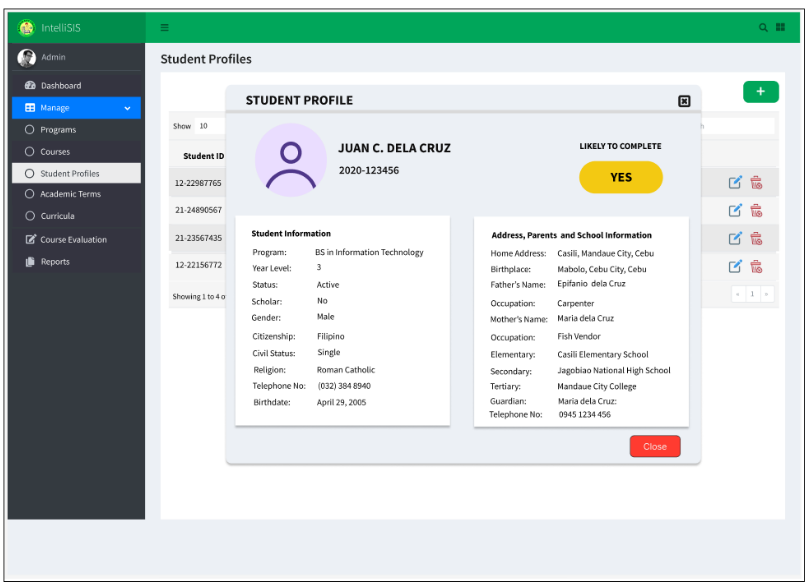

Figure 11: View Student Profile Details Screen

The figure above shows the view student profile details screen design which displays the information details of a particular student. The screen also displays the likelihood of completion on a program the student is currently taking up with.

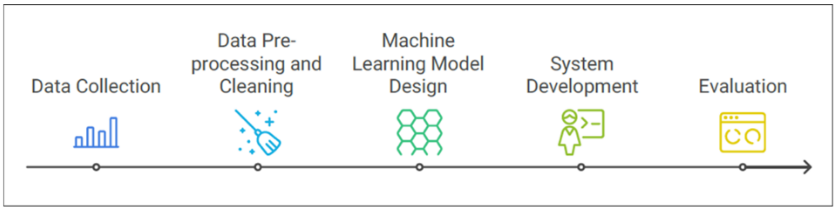

Figure 12: Machine Learning Model Development Steps

Building a machine learning model is a systematic process that involves several key steps. Each step is aimed at building a model that can make accurate predictions and provide insights. The figure above shows a breakdown of the process. The first step is the data collection, which will gather historical academic records, semestral grades, participation or affiliation in extracurricular activities, and demographic data of students from various sources in MCC which includes databases from existing systems, excel files and cabinet files. The second step is the data pre-processing and cleaning which includes organizing the student-related data for training the machine learning model. The step also includes data preparation activities such as removing duplicates, handling missing data, labeling and normalization. The third step is the model design wherein appropriate regression and classification algorithm will be selected. For IntelliSIS, logistic regression will be used to predict the likelihood that a particular student will be able to succeed on a program currently undertaken with. The next step is the system development wherein the integration of logistic regression into the system will take place. *The system* will have an interactive dashboard that will present the machine learning-driven insights in an easy-to-understand format or representation for school administrators, students and personnel users. The last step will be the evaluation where the system will be tested in MCC and the model predictions and optimizations will be compared with actual outcomes over time. For the model validation, the random holdout method will be used, which divides the dataset in 70% for training and 30% for testing. The model performance evaluation measures will be used which include accuracy, precision, recall and F1-Score.

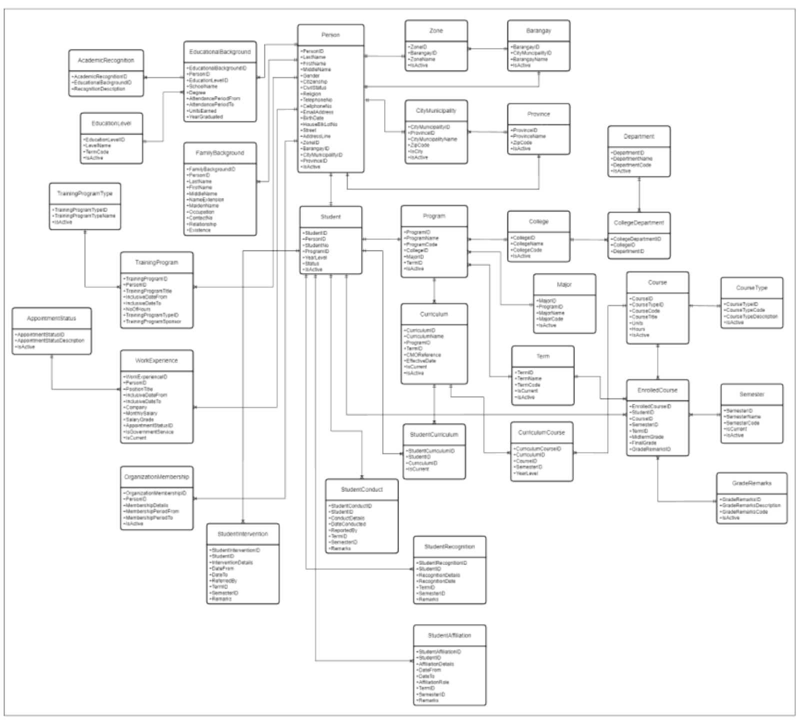

Figure 13: Data Model

For the database design, the data model above shows the relevant entities for the system. draw.io tool was used to create the data model. The specified entities will be then mapped to their equivalent database tables, which will store the needed student-related data and the data set to build up for the machine learning model.

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Development

In this phase, the system development involves the coding and implementation of IntelliSIS using various identified technology stacks as shown on the figure below. Specifically, the system will be a web application running on an Internet Information Services (IIS) Express via Microsoft Visual Studio as the main Integrated Development Environment (IDE).

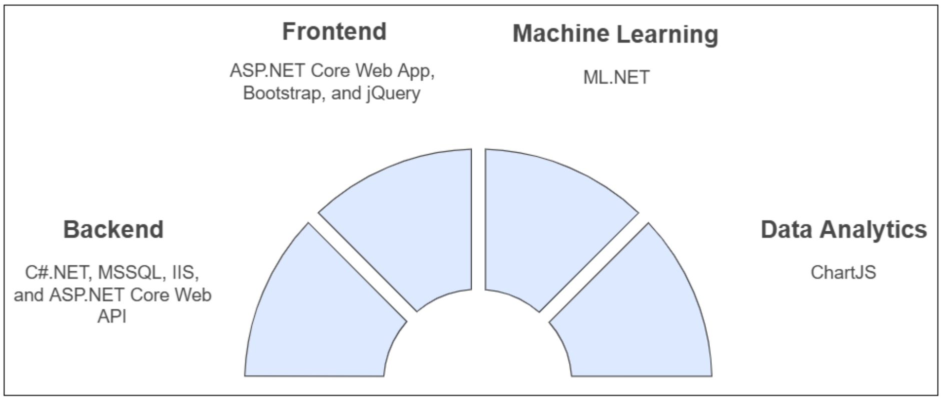

Figure 14: Technology Stack Diagram

In the system design phase, the actual development will focus on the implementation of major system components, including the backend, frontend, machine learning integration, and data analytics modules. The backend component involves the development of server-side logic using C#.NET, interaction with the database via Microsoft SQL Server (MSSQL), and the creation of API endpoints using the ASP.NET Core Web API framework with Entity Framework. The frontend component will be implemented using modern web technologies such as ASP.NET Core Web App, jQuery, and Bootstrap, ensuring that the system is dynamic, responsive, and compatible across various browsers.

For machine learning integration, logistic regression will be employed as the primary algorithm for both regression and classification tasks in predictive analytics. The integration will be facilitated by ML.NET, an open-source, cross-platform machine learning framework designed for .NET applications (Microsoft, n.d.). This will enable the system to function as an intelligent application capable of generating predictive insights. Lastly, the data analytics component will incorporate data visualization capabilities using the ChartJS JavaScript library, allowing key insights to be effectively displayed through the system's dashboard interface.

Testing

In this phase, IntelliSIS will be subject for evaluation ensuring the system meets the specified functional and non-functional requirements. System testing includes the conduct of unit testing, integration testing, machine learning model evaluation and User Acceptance Testing (UAT). The backend and frontend components will use NUnit, which is a unit testing framework for .NET. After conducting unit testing, integration testing will follow. This involves evaluation of how the identified IntelliSIS components will work together ensuring seamless integration. A test specification document will be prepared with identified test cases or scenarios, will be used for the conduct of integration testing. As mentioned previously, for the model evaluation, the random holdout method will be used, dividing the dataset with 70% for training and 30% for testing. The machine learning model will be evaluated with accuracy, precision, recall and F1-Score as the key performance metrics. Finally, acceptance testing or UAT will be conducted aided with a user acceptance document to validate and ensure that the system addresses the specific requirements and needs of the intended users specifically, the students and student service school personnel.

Deployment

In this phase, IntelliSIS will be deployed across designated environments to support final testing and production use. The primary objective of the deployment phase is to configure and validate the system within a staging environment prior to its official release in a live production setting. To facilitate this, the researchers intend to utilize SmarterASP.NET, a cloud hosting service that offers cost-effective plans in comparison to platforms such as Microsoft Azure and Amazon Web Services (SmarterASP.NET, n.d.). With the support of the hosting provider, both staging and production environments will be configured accordingly. The staging environment will serve as the platform for final or acceptance testing, ensuring that all system functionalities operate as expected under near-production conditions.

Once validated, the system will be deployed to the production environment for actual use. Moreover, end-users will be provided with comprehensive training sessions and supporting documentation to ensure effective system adoption and utilization.

Maintenance and Support

In this phase, IntelliSIS will undergo continuous monitoring activities to ensure optimal system performance and the effective handling of security concerns. Regular system updates will be implemented to address bugs or errors and to integrate additional features as needed. Furthermore, the system will undergo ongoing enhancements, facilitated by continuous coordination between the researchers and Mandaue City College (MCC), including systematic collection and analysis of user feedback to guide further improvements.

Results, Analyses and Discussion

The respondents answered the 20-item questionnaire and the statistical results are discussed and presented in the tables below. The interpretation of the mean of the survey is based on the following rating scale:

Table 2: Survey Mean Rating Scale

Description	Mean Range	Interpretation
Strongly Agree	3.25 – 4.00	Very High
Agree	2.50 – 3.24	High
Disagree	1.75 – 2.49	Low
Strongly Disagree	1.00 – 1.74	Very Low

1. Perception on the Current Status of the Management of Student Information

Table 3: Perception on the Current Status and Challenges of Managing Student Information

Item	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean	Standard Deviation
1.1 There has been an inconvenience in accessing and managing student-related data.	14%	80.6%	1.1%	4.3%	3.04	0.57
1.2 Student data handling during admissions and evaluations are manually processed and is said to be time-consuming.	30.2%	63.4%	3.2%	3.2%	3.2	0.65
1.3 Consolidating student academic records and generating student-related reports are inconvenient and difficult.	11.9%	81.7%	3.2%	3.2%	3.02	0.53
1.4 There has been difficulty in identifying academically challenged or at-risk students in the basis of their academic profile, data or information.	11.8%	76.4%	8.6%	3.2%	2.97	0.58
Average:					3.06	0.58

The result of the survey showed that the perception of the respondents towards the current status on how student information is managed consumes a lot of time specifically during admissions and evaluations is high with a mean of 3.2 and a standard deviation of 0.65. The overall perception of the respondents towards the current status and challenges on managing student information is high with a mean of 3.06 and a standard deviation of 0.58. This implies that the respondents generally agree on the current manual processes for managing student-related data are inefficient.

2. Perception on the Usefulness of IntelliSIS

Table 4: Perception on the Usefulness and Impact of IntelliSIS

Item	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean	Standard Deviation
2.1 The system will reduce manual processing and turnaround time on managing student-related data in the institution.	29.1%	64.5%	3.2%	3.2%	3.19	0.64
2.2 The system will improve student transactions and processes based on the policies and regulations in the institution.	26.9%	69.9%	0%	3.2%	3.21	0.6
2.3 The system will promote good reputation for various stakeholders on the provision of student-centered services and capabilities of the institution.	33.3%	63.5%	0%	3.2%	3.27	0.62
2.4 The system will support the institution's administrative and strategic management decisions and plans based on the data or information.	30.1%	66.6%	1.1%	2.2%	3.25	0.58
Average:					3.23	0.61

The result of the survey showed that the perception of the respondents towards the usefulness of IntelliSIS in MCC promotes good reputation to the institution through providing student-centered services is very high with a mean of 3.27 and a standard deviation of 0.62. The overall perception of the respondents towards the usefulness and impact of IntelliSIS is high with a mean of 3.23 and a standard deviation of 0.61. This implies that the respondents have strong optimism about the positive impact of a systemized student information system in the institution.

3. Perception on the Capabilities of IntelliSIS

Table 5: Perception on the Capabilities and Functionalities of IntelliSIS

Item	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean	Standard Deviation
3.1 The system will have the capability to provide consolidated student related information in an on-demand and real-time manner.	28%	64.5%	4.3%	3.2%	3.17	0.65
3.2 The system will have the capability to export and generate detailed student academic and administrative reports in various	33.4%	62.3%	1.1%	3.2%	3.25	0.64

Item						
formats (e.g. Word, PDF, CSV and Excel).						
3.3 The system will have security measures in preventing unauthorized access to student related information.	33.2%	62.4%	2.2%	2.2%	3.27	0.61
3.4 The system will support predictive analytics helping school personnel and administrators make data-driven decisions, determine at-risk students by forecasting the likelihood of completion or academic success in a chosen program or course.	28%	68.8%	0%	3.2%	3.22	0.6
Average:					3.23	0.63

The result of the survey showed that the perception of the respondents towards the capabilities of IntelliSIS in MCC assures security measures in preventing unauthorized access to student related information is very high with a value of 3.27 as the mean and a value of 0.61 as the standard deviation. The overall perception of the respondents towards the capabilities and functionalities of IntelliSIS is high with a value of 3.23 as the mean and a value of 0.63 as the standard deviation. This implies that the respondents indicate the significance of security, reporting and predictive analytics in meeting the expectations for the proposed system.

4. Perception of Factors Affecting Student Performance or Academic Success

Table 6: Perception of Student Performance or Academic Success Factors

Item	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean	Standard Deviation
4.1 Student performance or academic success comprises psychological or emotional factors.	28%	68.7%	1.1%	2.2%	3.23	0.57
4.2 Student performance or academic success comprises behavioral factors.	22.6%	74.1%	1.1%	2.2%	3.17	0.54
4.3 Student performance or academic success comprises participation or engagement in school-related or extra-curricular activities.	17.2%	78.5%	1.1%	3.2%	3.1	0.55
4.4 Student performance or academic success comprises scholastic evaluation, or the grades incurred from several courses or subjects on a chosen program.	22.6%	75.2%	0%	2.2%	3.18	0.53
Average:					3.17	0.55

The result of the survey showed that the perception of the respondents towards the factors affecting student performance or academic success includes non-academic attributes such as psychological or emotional factors is high with a value of 3.23 as the mean and a value of 0.57 as the standard deviation. The overall perception of the respondents towards the factors affecting student performance or academic success is high with a value of 3.17 as the mean and a value of 0.55 as the standard deviation. This implies that the respondents have a strong level of agreement in which student performance or academic success is determined by multidimensional factors.

5. Perception on the Challenges of Adopting IntelliSIS

Table 6: Perception on the Challenges of Adopting and Utilizing IntelliSIS

Item	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean	Standard Deviation
5.1 The current system on student admission and enrollment processes in the institution has been already practiced and adopted.	12.9%	82.7%	2.2%	2.2%	3.07	0.48
5.2 Utilization of systemized student information will require training for the assigned personnel and other affected stakeholders in the institution.	17.2%	80.6%	0%	2.2%	3.13	0.49
5.3 There is inadequate internal audit, administrative, management and student support in the institution.	11.8%	81.7%	4.3%	2.2%	3.03	0.5
5.4 The institution will be overwhelmed for the transition towards systemization of the consolidation or centralization of student information or records.	12.9%	82.7%	2.2%	2.2%	3.07	0.48
Average:					3.08	0.49

The result of the survey showed that the perception of the respondents towards the challenges of adopting IntelliSIS in MCC requires training for the assigned personnel or other users in the institution is high with a mean of 3.13 and a standard deviation of 0.49. The overall perception of the respondents towards the challenges of adopting and utilizing the student information system is high with a mean of 3.08 and a standard deviation of 0.49. This implies that the respondents highlight the importance of institutional readiness, training and support mechanisms to ensure a successful transition to a systemized student information system.

Conclusion and Recommendation

With the results presented in this study, it was found that the appreciation or insights of the respondents in the design and implementation of IntelliSIS in MCC is high and most of them highlight the importance of robust planning addressing critical challenges, comprehensive training for system utilization and a structured implementation approach for system development as they expect improvement in process efficiency, data security and decision-making through analytics. Furthermore, it can also be highlighted the importance of addressing factors influencing student performance or academic success including multidimensional factors including psychological, behavioral and academic dimensions. It is therefore recommended that the design and implementation of IntelliSIS in MCC should be further pursued as the proposed system addresses critical challenges, meets stakeholder expectations and aligns with the institutional goals anchored towards the Strategy Map 2027 of the Mandaue City Government to provide better support services to the students. The system will be a potential innovative solution which can be a technological model for other local higher educational institutions requiring structured development approach, support from stakeholders, transition management and the support and monitoring of student programs and services.

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