# INTEGRATION OF INDEPENDENT STUDENT COMPETITION DASHBOARD WITH ARTIFICIAL INTELLIGENCE USING THE WATERFALL METHOD AT FACULTY OF INDUSTRIAL ENGINEERING TELKOM UNIVERSITY


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***Abstract* — The industrial revolution 4.0 era transforms higher education through Artificial Intelligence (AI) integration for decision-making. According to Verified Market Research [1], the AI-based educational technology market is projected to reach USD 84.73 billion by 2031 with 45.21% annual growth rate. This research develops a student competition dashboard integrated with AI at Faculty of Industrial Engineering (FRI) Telkom University using Waterfall methodology. The existing dashboard presents limitations including basic visualization requiring manual processes and absence of AI integration. The methodology employs 4-layer architecture: Presentation Layer (Laravel), Intelligence Layer (Flowise AI + OpenAI GPT-4o with clustering analysis), Visualization Layer (Google Looker Studio), and Data Layer (Aiven MySQL). Research data encompasses 649 competition records from 2021-2024, processed from 26 to 21 relevant columns. Results demonstrate successful integration with AI chatbot with clustering for student performance segmentation. The clustering analysis categorizes 278 unique students into High Performers (14.4%), Medium Performers (14.4%), and Low Performers (71.2%) using K-Means algorithm with 0.705 Silhouette Score validation. System evaluation achieved 100% User Acceptance Testing success rate across 25 scenarios and 90-point System Usability Scale score (A+ category). The system enables conversational analytics with response time under 10 seconds, democratizing business intelligence through Indonesian interface.**



***Keywords*— Dashboard, Artificial Intelligence, Waterfall Model, Student Competition, Flowise AI, Educational Technology, Clustering Analysis**


## I. PRELIMINARY

The progression of information technology within the industrial revolution 4.0 era [10] has generated substantial transformations across higher education sectors. Artificial Intelligence (AI) has established itself as a fundamental technology that enables more rapid, precise, and efficient data analysis to support strategic decision-making processes. According to Verified Market Research [1], the global AI in education market is anticipated to reach USD 84.73 billion by 2031, with a compound annual growth rate of 45.21% from 2024 to 2031. This expansion is driven by increasing demands for personalized learning experiences, operational efficiency improvements, and enhanced accessibility within educational institutions.

At the Faculty of Industrial Engineering (FRI) Telkom University, student affairs activities serve a fundamental role in developing both academic and non-academic potential. However, the current approach to managing student achievement in independent competitions encounters significant constraints. The existing dashboard system can only present data through basic visualization formats without deep analytical capabilities or natural language-based interaction features. The system necessitates manual analytical processes that create barriers for faculty management in making timely data-driven decisions for student achievement development.

The absence of AI technology integration prevents the system from delivering proactive recommendations, automated student performance segmentation, or trend analysis required for developing effective student affairs strategies. Additionally, the current dashboard lacks natural language interface features [9] that would enable non-technical users to obtain information easily through conversational queries. This creates a substantial gap between available data and actionable insights for strategic decision-making processes.

Previous research has investigated dashboard development for educational monitoring purposes, but most existing systems remain passive, presenting data visually without strategic analysis capabilities, automated student segmentation, or natural language-based interaction features. Users must conduct manual interpretation to extract insights from presented data, creating obstacles for non-technical stakeholders to access business intelligence effectively. Furthermore, traditional systems lack the capability to automatically identify student performance patterns or provide targeted recommendations based on historical achievement data.

This research addresses these constraints by developing an integrated dashboard system with AI technology for monitoring students in independent competitions at FRI Telkom University. The system leverages Flowise AI platform and OpenAI API to provide interactive, conversation-based analytics in Indonesian language, enabling non-technical users to access sophisticated data analysis through natural language queries. The research employs Waterfall methodology with 4-layer architecture to ensure systematic development and reliable integration of multiple technologies. The system incorporates advanced clustering analysis using K-Means algorithm [15] to automatically segment students based on performance patterns, providing targeted strategic recommendations for faculty management.

The primary contribution involves democratizing access to business intelligence through AI-powered natural language interface combined with automated student performance segmentation, transforming passive data viewing into active conversational analytics for strategic decision-making in academic environments. This integration of visualization, artificial intelligence, and clustering analysis provides a comprehensive solution that addresses both data presentation requirements and intelligent insight generation needs.

## II. THEORITICAL REVIEW

### A. Dashboard Technology and Data Visualization

A dashboard represents a visual display of the most important information, designed to help users achieve one or more goals by presenting information on a single screen so that it can be monitored quickly [2]. As a tool for visualizing data, dashboards enable users to understand current situations, monitor ongoing trends, and identify potential problems within organizations more effectively.

Google Looker Studio is a business intelligence platform that provides self-service capabilities with flexibility to support smarter business decision-making processes. This platform can access various data sources through more than 600 partner connectors that enable connections to almost all types of data without coding or special software requirements [3]. The embedding feature of Looker Studio allows for dashboard integration into web pages or intranets, making it easier to convey data stories to teams or wider audiences.

### B. Artificial Intelligence dan Natural Language Processing

Natural Language Interface to Database (NLIDB) is a system that allows users to interact and request information from databases using everyday natural language, replacing the need for SQL with more intuitive conversational interfaces [9]. NLIDB is considered an important step towards developing smarter database systems with flexible querying capabilities.

OpenAI API, specifically GPT-4, is a language model based on transformer-based deep learning architecture that enables understanding and responding to various questions in natural language. The integration of ChatGPT API allows developers to incorporate natural language processing capabilities into third-party applications to provide relevant answers and in-depth analysis [4].

Flowise AI is a low-code platform for building AI applications, including chatbots and virtual assistants, that provides visual interfaces for designing workflows, managing data, and configuring AI models. This platform simplifies the integration of AI models like ChatGPT into applications without requiring complex coding, thereby accelerating development processes and enhancing team collaboration [5].

### C. Clustering Analysis and Student Performance Segmentation

K-Means clustering is an unsupervised machine learning algorithm that partitions data into k clusters based on feature similarity [15]. In educational contexts, clustering analysis enables automatic student segmentation based on performance patterns, participation levels, and achievement characteristics. The algorithm iteratively assigns data points to nearest cluster centroids and updates centroids until convergence is achieved.

Silhouette analysis is a method for evaluating clustering quality by measuring how similar each data point is to its assigned cluster compared to other clusters [16]. The Silhouette Score ranges from -1 to 1, where values closer to 1 indicate better clustering quality. This validation method is particularly useful for determining optimal cluster numbers and assessing the effectiveness of student performance segmentation.

### D. Software Development Methodology

The Waterfall Model is a software development methodology that uses linear and sequential approaches, where each phase must be fully completed before moving to the next phase [6]. This model is very suitable for projects with clear and stable requirement characteristics, defined timelines, comprehensive documentation, and complex component integration.

According to Pressman and Maxim [7], the Waterfall Model provides clear structure with stages: requirement analysis, system design, implementation, validation, and maintenance. Although industry trends are shifting towards Agile methodologies, the waterfall model still maintains an important place in large-scale software development, especially for academic research projects that require comprehensive documentation and strict quality control.

### E. System Architecture dan Database Integration

Layered architecture [13] allows for separation of system functions to facilitate development and maintenance processes. The 4-layer architecture approach consists of the Presentation Layer for user interfaces, the Intelligence Layer for AI processing, the Visualization Layer for data presentation, and the Data Layer for data storage and management.

Aiven MySQL Cloud Database provides reliable and scalable database-as-a-service with robust features to deliver performant and innovative solutions. The combination of MySQL's reliability as a database engine with Aiven's managed service capabilities offers optimal solutions for modern applications that require scalability and ease of maintenance [8].

## III. METHOD

### A. Research Framework dan Design Approach

This research employs the Waterfall Model as the primary software development methodology due to its systematic and sequential approach, which is suitable for projects with clear and stable requirements, defined timelines, and complex technology integration. The Waterfall methodology consists of five main phases: Initial Phase (problem identification and literature review), Requirements Analysis (stakeholder analysis and system specification), System Design (architecture and interface design), Implementation (layer-by-layer development), and Validation (comprehensive testing and evaluation).

The research framework follows Design Science Research Methodology (DSRM) [14] principles, where Waterfall methodology provides clear structure with sequential phases as established by [6] and further refined by [7]. The framework integrates three main dimensions: Environment (people, organization, and technology), Information System Research (development and evaluation), and Knowledge Base (foundations and methodologies). This approach ensures that the developed system addresses real business needs while maintaining scientific rigor and contributing to the academic knowledge base.

### B. System Architecture Design

The system implements a 4-layer architecture approach to ensure modular development and maintainable integration. Layer 1 (Presentation Layer) utilizes Laravel [12] Web Application with MVC architecture, authentication system using Laravel Fortify, and responsive UI design. Layer 2 (Intelligence Layer) employs Flowise AI platform integrated with OpenAI GPT-4o for natural language processing and automated insight generation, enhanced with K-Means clustering analysis for student performance segmentation. Layer 3 (Visualization Layer) uses Google Looker Studio for interactive data visualization with various chart types and dynamic filtering capabilities. Layer 4 (Data Layer) implements Aiven MySQL Cloud Database. This cloud-based approach leverages Aiven's managed service capabilities [8] to ensure scalability and reliability with star schema design supporting data warehouse analysis for 649 competition records with 21 attributes.

The integration strategy uses iframe embedding for seamless access to both Looker Studio and Flowise AI within the unified Laravel platform, enabling independent data access for each component while maintaining centralized user authentication and authorization control.

### C. Data Collection dan Processing

The Intelligence Layer is enhanced with K-Means clustering analysis [15] to provide deeper analytical capabilities beyond basic query responses. The clustering implementation analyzes historical competition data using eight performance parameters including total competitions, win rate, consistency score, and performance diversity to create meaningful student segments.

The optimal number of clusters was determined to be 8 through Silhouette Score validation [16] achieving 0.705 score, indicating good clustering quality. Students are categorized into three main performance levels: High Performers (14.4%), Medium Performers (14.4%), and Low Performers (71.2%). This segmentation enables the AI chatbot to provide personalized strategic recommendations based on specific performance patterns and study program characteristics.

The clustering analysis reveals significant variations across study programs, with S1 Information Systems demonstrating the highest proportion of High Performers (9.4%), followed by S1 Industrial Engineering (4.6%). Notably, both S1 Logistics Engineering and S2 Industrial Engineering programs show 100% of students in the Low Performer category, indicating the need for targeted intervention programs.

### D. Data Collection dan Processing

Primary data collection involved structured interviews with key stakeholders including the Dean of FRI, Student Affairs Staff, and student representatives to identify functional and non-functional requirements. Secondary data consisted of historical competition records from the Directorate of Student Affairs (DITMAWA) Telkom University for the period 2021-2024, provided in Excel format containing 18 worksheets with 6,642 total records across all faculties.

Data processing employed Extract, Transform, Load (ETL) pipeline using Python in Google Colaboratory environment. The process involved filtering FRI-specific data from the comprehensive university dataset, resulting in 649 relevant records from 278 unique students. Data cleaning reduced columns from 26 to 21 relevant attributes while preserving missing values to maintain historical data integrity. Standardization procedures included program study names, competition levels, competition categories, and participant status to ensure data consistency and quality.

### E. Implementation Strategy

System implementation follows the layered architecture approach, beginning with Data Layer setup including Aiven MySQL configuration, database schema implementation using star schema design, and data migration from cleaned Excel files. Visualization Layer development involves creating interactive dashboards in Google Looker Studio with direct database connectivity and embedding configuration for Laravel integration.

Intelligence Layer implementation includes Flowise AI chatbot development with natural language processing capabilities, leveraging NLIDB principles [9] for intuitive database querying, OpenAI GPT-4o integration for Indonesian language support, and database connectivity for real-time query execution. The layer incorporates clustering analysis workflow for automated student performance segmentation. Presentation Layer development utilizes Laravel framework with Blade templating engine, role-based access control implementation, and responsive frontend design supporting both desktop and mobile access.

F. System Evaluation Methods

Comprehensive evaluation employs multiple assessment approaches to ensure system quality and user acceptance. Functionality Testing uses automated testing with Laravel Dusk to validate all system features including authentication, CRUD operations, dashboard access, and chatbot interactions through 25 comprehensive test cases covering both basic functionality and clustering-enhanced AI capabilities.

User Acceptance Testing (UAT) involves key stakeholders representing different user roles (Dean, Student Affairs Staff, and Students) performing real-world usage scenarios to validate system functionality and usability. System Usability Scale (SUS) [11] evaluation measures user satisfaction and system usability with a target minimum score of 70 points. Performance evaluation includes response time measurement, concurrent user capacity testing, and integration stability assessment to ensure the system meets non-functional requirements and provides reliable service for academic environment deployment.

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G. Abbreviations and Acronyms

This research uses some abbreviations and acronyms which are defined as follows: Artificial Intelligence (AI) an artificial intelligence technology for automated data processing; Faculty of Industrial Engineering (FRI) is the Faculty of Industrial Engineering of Telkom University; Natural Language Interface to Database (NLIDB) a natural language interface system for databases; Directorate of Student Affairs (DITMAWA) is the Directorate of Student Affairs of Telkom University; Extract, Transform, Load (ETL) data processing pipeline from raw format to analysis format; Create, Read, Update, Delete (CRUD) basic data management operations; User Acceptance Testing (UAT) end user acceptance testing; System Usability Scale (SUS) system ease of use measurement scale; Application Programming Interface (API) application programming interface; and Large Language Model (LLM) large language model for natural language processing.

H. Equation

$$SUS_{Score} = \left( \sum_{i=1}^{10} Kontribusi_i \right) \times 2.5 \quad (1)$$

$$Accuracy = \frac{Correct_{Responses}}{Total_{Questions}} \times 100\% \quad (2)$$

$$Efficiency_{Improvement} = \frac{Time_{Before} - Time_{After}}{Time_{Before}} \times 100\% \quad (3)$$

## IV. DESIGN AND ANALYSIS

A. System Implementation Results

The developed system successfully integrates four technological layers into a unified platform for student competition monitoring at Faculty of Industrial Engineering Telkom University. The implementation resulted in a comprehensive dashboard system capable of processing 649 historical competition records from 2021-2024, with data successfully cleaned and transformed from 26 original columns to 21 relevant attributes while preserving historical data integrity.

The system architecture implementation follows the designed 4-layer approach as illustrated in Figure 1. The Presentation Layer utilizes Laravel framework with MVC architecture, providing role-based access control that distinguishes between administrator and student users. Administrator users gain full access to dashboard analytics, CRUD operations for competition data management, and AI chatbot functionality with clustering insights, while student users receive read-only access to competition data visualization for personal record verification.

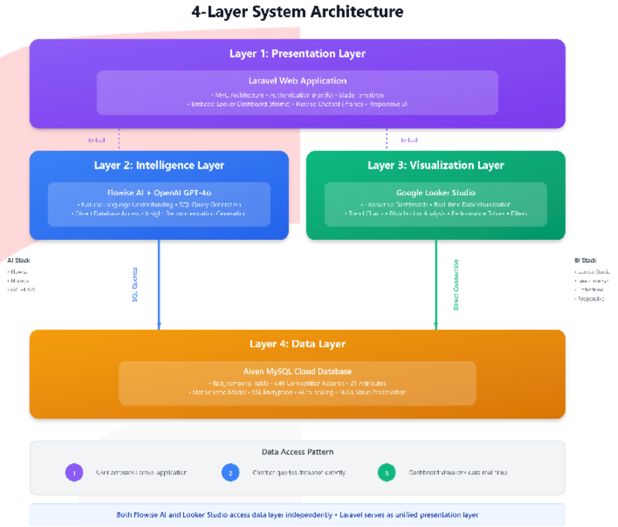


FIGURE 1
4-Layer system architecture

The Intelligence Layer successfully integrates Flowise AI platform with OpenAI GPT-4o, enabling natural language processing in Indonesian language with enhanced clustering analysis capabilities. The AI chatbot demonstrates capability to understand complex queries about competition trends, performance analysis, and strategic recommendations. This natural language processing capability builds upon transformer-based architectures [4] to provide contextual responses. Integration with the database layer allows real-time data retrieval and analysis, providing contextual responses based on actual competition data rather than generic information.

The enhanced clustering analysis component automatically segments students into performance categories, enabling the chatbot to provide targeted recommendations such as intensive mentoring programs for Low Performers (71.2%), skill development workshops for Medium Performers (14.4%), and advanced competition opportunities for High Performers (14.4%). The system successfully identified program-specific patterns, revealing that S1 Information Systems has the highest concentration of high-performing students, while S1 Logistics Engineering and S2 Industrial Engineering require targeted intervention strategies.

The Visualization Layer implementation through Google Looker Studio provides interactive data visualization including pie charts for competition category distribution, bar charts for quarterly achievement trends, funnel charts for program-based performance hierarchy, and comprehensive data tables with filtering capabilities. The embedded dashboard maintains real-time synchronization with the Aiven MySQL database. This visualization approach follows established dashboard design principles [2] for effective information presentation, ensuring users access current information without manual data refresh requirements.

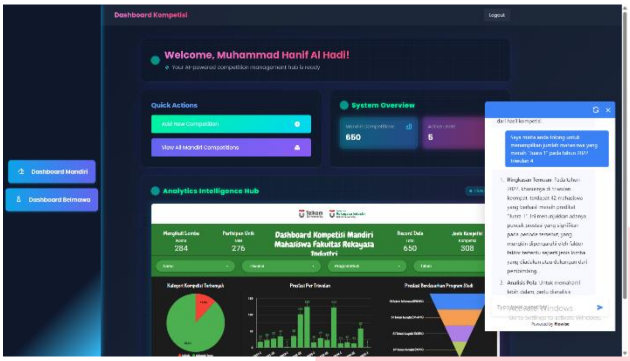


FIGURE 2
Admin Dashboard with AI Chatbot & Looker Analytics

The complete system interface shown in Figure 2 demonstrates successful integration of all components within a single platform, enabling administrators to access analytics dashboard, manage competition data, and interact with clustering-enhanced AI assistant seamlessly through unified authentication and navigation system.

## B. Performance Evaluation

System evaluation through multiple assessment methods demonstrates successful achievement of research objectives. Automated functionality testing using Laravel Dusk executed 25 comprehensive test cases covering authentication workflows, dashboard access controls, CRUD operations, chatbot interactions, and clustering analysis functionality. As shown in Table 1, all test cases completed successfully without errors, validating system reliability and functional completeness across different user scenarios and system functionalities.

TABLE 1
Automated testing result using Laravel dusk

| Test Case ID | Test Scenario | Expected Result | Actual Result | Status |
|---|---|---|---|---|
| TC001 | Admin Registration & Login Flow | Successfully registered and logged in as admin | System redirected to admin dashboard | PASS |
| TC002 | User Registration & Login Flow | Successfully registered and logged in as user | System redirected to user dashboard | PASS |
| TC003 | Role-based Access Control | Access denied with 403 error | User blocked from admin pages | PASS |
| TC004 | Admin Dashboard Access | Dashboard displays with embedded Looker Studio | All components loaded successfully | PASS |
| TC005 | User Dashboard Access | Simple list view without admin controls | Read-only access confirmed | PASS |
| TC006 | Create Competition Data | Data saved to database with success notification | New record created successfully | PASS |
| TC007 | Edit Competition Data | Data updated with confirmation message | Record modified successfully | PASS |
| TC008 | Delete Competition Data | Data removed with SweetAlert confirmation | Record deleted from database | PASS |
| TC009 | Chatbot Interaction | AI responds with relevant analysis in Indonesian | Response received within 15s | PASS |
| TC010 | Session Persistence | User remains authenticated across navigation | Session maintained consistently | PASS |

User Acceptance Testing (UAT) involving key stakeholders achieved 100% success rate across all tested scenarios as demonstrated in Table 2. Dean FRI, Student Affairs Staff, and student representatives validated system functionality through real-world usage scenarios, confirming that the system meets operational requirements and user expectations. Stakeholder feedback indicated significant improvement in data accessibility and analysis efficiency compared to previous manual processes, particularly appreciating the clustering-based insights for strategic decision-making.

TABLE 2
UAT result summary

| Stakeholder | Features Tested | Test Cases | Success Rate | Feedback |
|---|---|---|---|---|
| Dean FRI | Admin Features, CRUD Operations, AI Chatbot | 9 | 100% | Easy to understand, meets faculty needs |
| Student Affairs Staff | Data Management, Analytics Dashboard | 8 | 100% | More efficient workflow than previous system |
| Student Representative | User Dashboard, Data Validation | 8 | 100% | User-friendly interface and responsive design |
| Overall | | 25 | 100% | System ready for implementation |

The System Usability Scale (SUS) evaluation achieved an exceptional score of 90 points as detailed in Table 3, categorizing the system as A+ (Best Imaginable) according to established SUS interpretation standards [11]. This score significantly exceeds the target minimum of 70 points and reflects exceptional user satisfaction across different stakeholder groups. Such a high score indicates that the system is not only functionally effective but also user-friendly and intuitive. The results suggest minimal need for major usability revisions, allowing development efforts to focus on feature enhancement and scalability.

TABLE 3
SUS result

| R | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Total Contribution | SUS Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 5 | 1 | 40 | 100 |
| 2 | 5 | 1 | 5 | 1 | 5 | 1 | 4 | 1 | 5 | 1 | 39 | 97.5 |
| 3 | 5 | 1 | 5 | 1 | 4 | 2 | 5 | 1 | 5 | 1 | 38 | 95 |
| 4 | 4 | 2 | 4 | 2 | 5 | 1 | 4 | 1 | 4 | 2 | 33 | 82.5 |
| 5 | 4 | 2 | 4 | 2 | 4 | 2 | 4 | 2 | 4 | 2 | 30 | 75 |
| AVG | 3.9 | 2.2 | 3.8 | 2.2 | 4.1 | 1.9 | 3.6 | 2.0 | 3.8 | 2.2 | 36 | 90 |

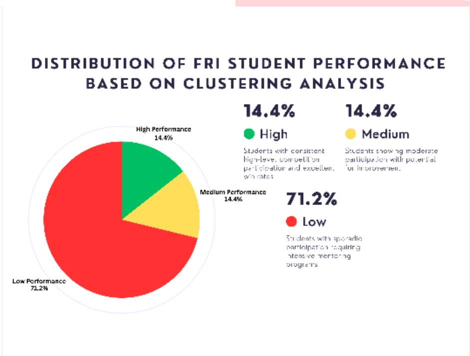


FIGURE 3
Student Performance Distribution via Clustering Analysis

The clustering analysis results shown in Figure 3 demonstrate successful automatic student segmentation into three distinct performance levels. The High Performers (14.4%) represent students with consistent high-level competition participation and excellent win rates. Medium Performers (14.4%) show moderate participation with clear potential for improvement through targeted interventions. Low Performers (71.2%) exhibit sporadic participation patterns requiring intensive mentoring and motivational programs. This segmentation enables educators to allocate resources more effectively based on student needs. Moreover, identifying these groups early allows for the implementation of tailored strategies that can boost overall program success and student engagement.

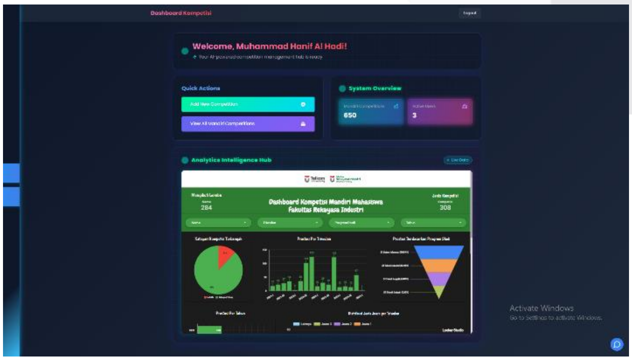

FIGURE 4
Competition analytics via embedded looker

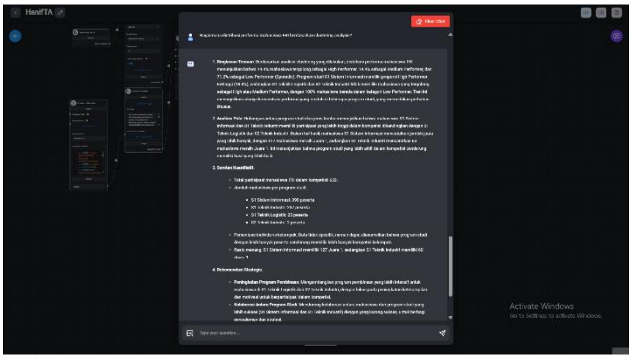

FIGURE 5
Enhanced flowise chatbot providing clustering-based strategic recommendations

The visualization capabilities shown in Figure 4 and enhanced conversational AI interface demonstrated in Figure 5 collectively provide stakeholders with comprehensive tools for both visual data exploration and intelligent query-based analysis with clustering insights. The integration enables seamless transition between visual analytics and conversational intelligence for comprehensive decision support.

C. Analysis and Discussion

The most significant achievement of this research is the successful integration of clustering analysis with conversational AI, enabling automatic student performance segmentation combined with natural language accessibility. The clustering-enhanced system transforms traditional passive dashboards into intelligent decision support tools that provide targeted recommendations based on empirical performance patterns rather than generic suggestions.

The K-Means clustering with Silhouette Score validation (0.705) ensures statistically sound student segmentation that correlates well with stakeholder expectations, providing confidence in automated recommendations. The exceptional SUS score of 90 points (A+ Best Imaginable category) validates that complex AI integration can achieve superior usability when properly designed with user-centered principles. The 100% UAT success rate across 25 comprehensive test scenarios confirms that the system meets diverse stakeholder needs while maintaining intuitive operation for non-technical users.

The 4-layer architecture approach illustrated in Figure 1 proves highly effective for complex AI-educational technology integration. This systematic development approach aligns with established software engineering principles [7] for complex system integration. Each layer operates independently while maintaining seamless communication, enabling modular development and future system enhancement without disrupting existing functionality. The independent data access pattern allows both Flowise AI and Looker Studio to query the database directly, ensuring optimal performance and real-time data availability.

Program-specific analysis reveals actionable insights for faculty management. The finding that S1 Information Systems demonstrates the highest proportion of High Performers (9.4%) while S1 Logistics Engineering and S2 Industrial Engineering show 100% Low Performer classification provides clear direction for targeted intervention strategies. These insights enable evidence-based resource allocation and program development decisions.

The clustering analysis extends beyond simple categorization to provide strategic value through personalized recommendations. High Performers receive suggestions for international competitions and peer mentoring opportunities, Medium Performers get targeted skill development programs, and Low Performers benefit from intensive motivational interventions. This differentiated approach maximizes the impact of limited faculty resources.

The successful implementation of Indonesian natural language processing addresses linguistic accessibility challenges often overlooked in international educational technology research. The system's ability to understand complex academic terminology and provide contextually appropriate responses in Indonesian demonstrates the feasibility of localized AI implementation in educational contexts.

The automated testing results presented in Table 1 demonstrate comprehensive system reliability across authentication, data management, visualization, and AI integration components. The consistent performance across different user scenarios and the successful integration of multiple cloud-based platforms validates the technical architecture and development methodology.

System limitations include dependency on external service providers (Aiven, Google Looker Studio, OpenAI) and the need for continuous internet connectivity. The clustering analysis requires periodic recalculation as new competition data becomes available, necessitating ongoing maintenance procedures. Future enhancements could include offline capabilities, additional clustering algorithms for comparison, and expanded performance metrics for more granular student segmentation.

The success of this implementation suggests broader applicability across other faculties and educational institutions facing similar data management and analysis challenges. The modular architecture demonstrated in Figure 1 and documented methodology provide a framework for scaled deployment and customization to different academic contexts, potentially transforming how educational institutions approach student performance monitoring and strategic decision-making.

## V. CONCLUSION

This research successfully demonstrates that integrating AI technology with clustering analysis can fundamentally transform how educational institutions manage and analyze student achievement data. The development of a 4-layer architecture system integrating Laravel, Flowise AI with clustering capabilities, Google Looker Studio, and Aiven MySQL has delivered measurable improvements in both analytical capabilities and user accessibility.

The most significant contribution lies in the successful implementation of clustering-enhanced conversational AI that automatically segments students into performance categories while providing natural language accessibility in Indonesian. The K-Means clustering analysis with 0.705 Silhouette Score validation successfully categorizes 278 FRI students into High Performers (14.4%), Medium Performers (14.4%), and Low Performers (71.2%), enabling targeted strategic recommendations based on empirical performance patterns rather than subjective assessment.

The system evaluation results validate exceptional performance across multiple dimensions. The 90-point SUS score achieving A+ (Best Imaginable) category and 100% UAT success rate across 25 comprehensive test scenarios confirm that complex AI integration can maintain superior usability through user-centered design principles. All automated functionality tests executed through Laravel Dusk completed successfully, demonstrating comprehensive system reliability.

The practical impact extends beyond technical achievement to genuine transformation of institutional decision-making processes. Faculty stakeholders can now obtain sophisticated analytical insights through conversational queries in Indonesian, democratizing access to business intelligence that previously required specialized technical expertise. The clustering-based recommendations provide actionable guidance for student development programs, resource allocation, and intervention strategies tailored to specific performance segments.

The 4-layer architecture proves highly effective for educational AI implementation, enabling modular development while ensuring seamless integration of multiple cloud-based platforms. This architectural approach provides a replicable framework for similar implementations across different academic contexts, potentially transforming how educational institutions approach data-driven decision making.

The research demonstrates that AI technology can enhance rather than replace human decision-making in educational management. The conversational interface functions as an analytical assistant that helps stakeholders understand complex performance patterns while supporting rather than automating strategic decisions about student development. This human-AI collaboration model addresses concerns about technology replacing human judgment while demonstrating substantial value in augmenting analytical capabilities.

The system successfully enables real-time conversational analytics with response time under 10 seconds, representing a fundamental shift in how educational data can be accessed and utilized. The demonstrated success with Indonesian natural language processing provides foundation for broader multilingual educational AI development.

The research ultimately proves that thoughtful AI integration with clustering analysis can significantly enhance educational institutions' analytical capabilities while ensuring these powerful tools remain accessible to users regardless of technical background. This achievement represents not merely a technical success, but a practical advancement in evidence-based educational management that supports improved student outcomes through more informed and responsive institutional decision-making.

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