Jurnal Sosioteknologi, Volume 25, No. 2, July 2026

KKIK - FSRD

Jurnal Sosioteknologi

Website: https://journals.itb.ac.id/index.php/sostek/index

Socio-Technological Business Intelligence Dashboard for Academic Quality Assurance Using Design Thinking and Kimball Approach

Dashboard Business Intelligence Sosio-Teknologi untuk Penjaminan Mutu Akademik Menggunakan Design Thinking dan Pendekatan Kimball

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https://doi.org/10.5614/sostek.itbj.2026.25.2.4
Submitted: December 29, 2025 Accepted: June 23, 2026 Published: July 31, 2026

ARTICLE INFO

Keywords:
business intelligence, sentiment analysis, four-step Kimball, power BI, academic quality assurance

ABSTRACT

Academic quality assurance (QA) in higher education institutions (HEIs) typically relies on conducting student surveys every semester to evaluate lecturer performance. However, the data processing in the case study remains manual in Microsoft Excel. Data processing results in 3 to 4 days of reporting delay per cycle. There are issues with data inconsistency, duplication, and non-automated mapping of questions into variables. This study aims to develop a business intelligence (BI) dashboard using Power BI that supports data-driven academic QA. The system was developed using human-centered design thinking and the four-step Kimball data warehousing methodology. The resulting dashboard comprises six main pages incorporating Python-based sentiment analysis. This dashboard includes interactive filtering and automated mapping of question variables. Evaluation through task-based usability testing yielded a 100% task completion rate, an average Single Ease Question score of 6.08 out of 7, and 100% data validity within a ±0.01 tolerance. In addition, all 43 visuals load in under 500 milliseconds. Theoretically, this study contributes a validated socio-technical BI framework demonstrating that user-participatory development has implications for organizational culture and decision-making in vocational HEIs. Practically, this dashboard eliminates manual reporting bottlenecks and enables stakeholders to monitor lecturer performance and generate reports more efficiently.

INFO ARTIKEL

Kata kunci:
business intelligence*, analisis sentimen,* four-step Kimball, Power BI, *Penjaminan Mutu Akademik*

ABSTRAK

Penjaminan Mutu Akademik (QA) di lembaga pendidikan tinggi biasanya melakukan survei pada mahasiswa setiap semester untuk mengevaluasi kinerja dosen. Namun, pengolahan data dalam studi kasus masih dilakukan secara manual menggunakan Microsoft Excel*. Pengolahan data mengakibatkan keterlambatan pelaporan tiga hingga empat hari per siklus. Terdapat masalah inkonsistensi data, duplikasi, serta pemetaan pertanyaan ke variabel yang tidak otomatis. Studi ini bertujuan untuk* *mengembangkan dasbor* Business Intelligence (BI) *menggunakan* Power BI *yang berbasis pada data QA akademik. Sistem ini dikembangkan menggunakan* Human-Centered Design Thinking *dan Metodologi Kimball Empat Langkah. Dasbor yang dihasilkan terdiri dari enam halaman utama yang menggabungkan analisis sentimen berbasis* Python. *Dasbor mencakup penyaringan interaktif dan pemetaan variabel pertanyaan secara otomatis. Evaluasi melalui Pengujian Usabilitas Berbasis Tugas menghasilkan tingkat penyelesaian tugas 100%, skor Pertanyaan Kemudahan Tunggal rata-rata 6,08 dari 7, serta validitas data 100% dengan toleransi ±0,01. Selain itu, semua 43 visual dimuat dalam waktu kurang dari 500 milidetik. Secara teoritis, studi ini memberikan kerangka kerja BI sosio-teknis yang valid dan menunjukkan bahwa pengembangan partisipatif pengguna memiliki implikasi terhadap budaya organisasi serta pengambilan keputusan di lembaga pendidikan tinggi vokasi. Secara praktis, dasbor ini menghilangkan hambatan pelaporan manual dan memungkinkan pemangku kepentingan memantau kinerja dosen serta menghasilkan laporan dengan lebih efisien.*

Introduction

Quality assurance in Higher Education Institutions (HEIs) is a fundamental determinant of institutional sustainability, giving value and competitiveness. HEIs in Indonesia are required to implement the Internal Quality Assurance System (namely SPMI). The SPMI process is regulated by the Minister of Higher Education, Science, and Technology Regulation No. 39 of 2025. According to Regita (2024), academic performance evaluation is especially crucial for measuring teaching capability, as it enables lecturers to enhance their competency in specific pedagogical areas and meet student expectations. Routine evaluation of teaching performance requires the use of valid instruments (Spooren et al., 2013). This evaluation is a crucial component for improving academic quality.

This research uses an experimental study to examine the importance of BI dashboards in higher education. Politeknik Caltex Riau (PCR) was chosen as a case study. PCR is a vocational education institution with outstanding accreditation. However, there are issues with the academic evaluation process, and the dashboard visualization needs improvement. This is because PCR's existing dashboard system still accommodates analytical results, which are increasingly demanding more than just static dashboards. Based on the issues identified by PCR, this research will develop a dashboard based on the analytical data presented.

Operationally, PCR encountered various obstacles, including technical constraints and the lengthy business processes required to obtain analysis results. The survey evaluation process utilized a website developed internally by the polytechnic. While the survey distribution process was digital, the results were still processed manually using Microsoft Excel. This manual process requires a significant amount of data processing time. This manual process posed a high risk of data inconsistencies, duplication, and formatting errors. Furthermore, the large volume of data generated each semester is particularly challenging (Nurmalasari & Nurzikriah, 2021). A deeper issue lies in the limited analytical flexibility of mapping survey questions to standard models, such as the Service Quality (SERVQUAL) model. The existing process is inefficient because question structures often change annually, requiring repetitive and error-prone manual adjustments (Nashihuddin, 2012). Manually processed QA results were then uploaded to a separate static dashboard system, distinct from the survey system. The problems with this old dashboard system were that it was static, lacked interactivity, and did not support in-depth analysis. The process of producing a comprehensive QA report was time-consuming and prone to human errors (Nurmalasari & Nurzikriah, 2021).

From a socio-technical perspective, the effectiveness of quality assurance systems is determined by technological capability that aligns with organizational workflows, human workflows, habits, and expectations of the people who use them (Bednar & Welch, 2020). Human behavior plays a central role in how information systems succeed or fail in practice; a technically well-designed dashboard will still be underused if it does not fit the way people work and make decisions. The format, completeness, and recency of information presented on a dashboard can significantly influence the quality of human decision-making, as people tend to rely more on systems that present information in ways that feel clear, credible, and immediately relevant to their tasks (Hjelle et al., 2024). Business intelligence (BI) has been proven to process available data using mathematical models to produce knowledge that supports complex decision-making (Vercellis, 2009). BI effectively provides strategic insights compared to conventional reporting methods (Mulyani et al., 2018; Najwa et al., 2023).

It is not uncommon for BI to remain underutilized by organizations due to the trust issues surrounding data analysis. Therefore, behavioral change and trust-building are necessary in using BI (Alkhwaldi et al., 2025). The socio-technical approach used in this study examines user behavior and their needs for BI. Users are involved in developing and defining charts for data visualization. This fosters greater user trust in the data transformation process, aligning with data analysis and reporting needs. By automating the ETL process through Power Query and applying validation rules at the data entry point, the system ensures that the information displayed on the dashboard accurately reflects the actual state of academic evaluation data. By applying design thinking concepts, visualizations are designed to meet the data information needs of each functional position. Visualization needs vary between structural and lecturer levels. Users can utilize this BI system accurately, in real time, dynamically, and to support decision-making.

When developing dashboards, organizations should prioritize user-centered design rather than focusing solely on visualization. Organizations can customize data visualizations based on the results of the question-and-answer (QA) survey for deeper analysis. User-centered dashboards have been shown to improve user satisfaction and system usability (Murtiastuti et al., 2023). The application of socio-technological concepts integrates both design thinking methods and the Four-Step Kimball Cycle methodology. The Design Thinking approach helps view dashboard needs from the user's perspective by emphasizing empathy to reduce bias. This approach strongly involves users in dashboard development (Zulaikha et al., 2023). The Design Thinking approach offers solutions that meet needs and reduce the risk of failure (Haddadian et al., 2019).

This research aims to develop an interactive academic QA dashboard at PCR. This dashboard development is expected to address current weaknesses in business processes. The development of a business intelligence (BI)-based dashboard integrates Kimball's approach with design thinking. The combination of these two methods has proven successful in improving automated and centralized performance monitoring (Azzahra et al., 2025). The resulting dashboard provides interactive analytics, longitudinal performance trends for each study program, and machine-learning-based sentiment analysis of student feedback. The developed dashboard system also automates the ETL (Extract, Transform, Load) process.

Although the adoption of BI tools in higher education institutions (HEIs) continues to increase, there remains a clear research gap. Previous studies have generally focused either on the application of design thinking in user interface development or on the use of the Kimball lifecycle for technical data modeling, but few have combined both approaches into a single integrated system for academic QA. In addition, most prior studies have focused solely on the technical implementation of BI tools without examining how the application of such technology changes work practices, roles, or decision-making culture within the organization. Studies developing QA dashboards for higher education institutions also rarely conduct evaluations using rigorous task-based usability methods or report quantitative performance metrics. Specifically in vocational higher education institutions in Indonesia, there is still limited evidence of BI-based QA systems that integrate automated sentiment analysis, dynamic mapping of EDOM (Student Evaluation of Lecturers) and SERVQUAL (Service Quality), and role-based access control within a single integrated platform. This absence of a social perspective is important because, in an educational environment, the adoption of digital technology not only automates tasks but also redefines how staff interact with data, how accountability is built, and how a culture of quality develops. This research aims to fill this gap by presenting the design, development, and evaluation of a comprehensive academic QA dashboard at PCR. This dashboard pays explicit attention to both technical performance and the socio-technological changes enabled by the system.

Method

This research was conducted to help optimize data processing and visualization processes through a BI system. There are two system perspectives in the system design process. First, the user perspective focuses on ensuring that the system aligns with existing needs and work practices. This perspective is addressed through the design thinking framework (Haddadian et al., 2019; Zulaikha et al., 2023). The second perspective concerns the technical aspects of system development and is addressed using Kimball's Four-Step methodology. The use of this methodology ensures that survey data is structured and can support flexible analysis (Kimball & Ross, 2013). The combination of these two approaches is illustrated in the research workflow presented below.

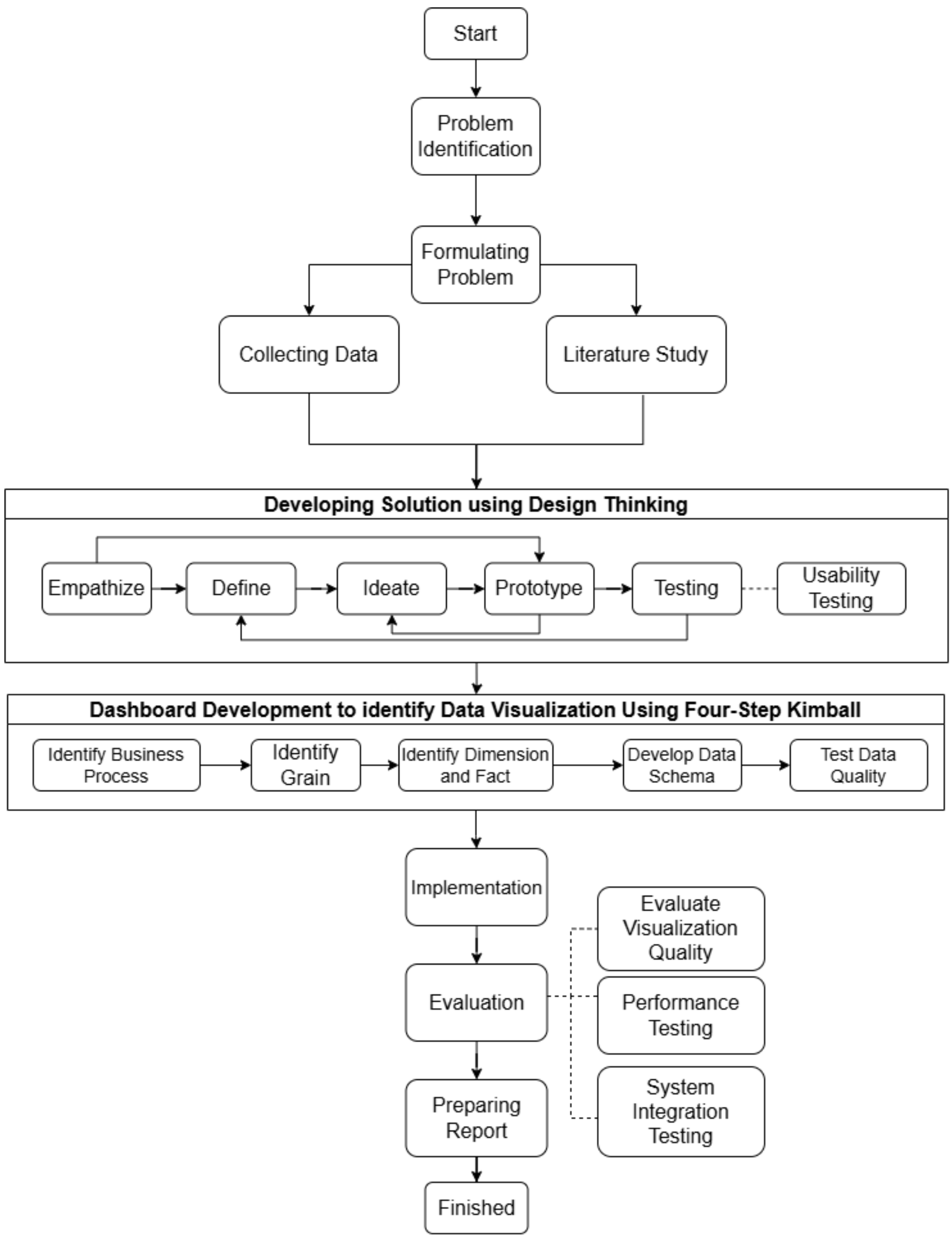

Figure 1 Research Methodology Workflow

Design Thinking

Each stage of the design thinking process actively involves users to ensure that the resulting dashboard solution effectively addresses the challenges of PCR in academic quality assurance evaluation, particularly the pain points users experience. The application of the design thinking approach in this research actively involves users. User involvement is useful for ensuring that the needs and suitability of the resulting data visualizations are met. This approach also allows for the definition of PCR problems in the academic evaluation process.

The first stage is empathy. This empathy definition process was conducted through a focus group discussion (FGD) on October 15, 2024. The FGD involved the head of internal quality assurance, the head of the study program, and an expert. This session was used to understand how survey data is currently accessed, processed, and utilized, as well as to identify specific difficulties associated with manual data processing. The empathy stage also yielded the information needs of each user group from the QA dashboard. The findings from this stage were then compiled and visualized using an empathy map.

The second stage is identification. This process focuses on formulating the main problems faced by stakeholders. Next, in the ideation stage, the research team conducted a brainstorming session using the "how might we" method. This stage generated various solution ideas, such as implementing an automated ETL (Extract, Transform, Load) process. Machine learning-based sentiment analysis and the development of an interactive dashboard with drill-down capabilities were also conducted. The ideation stage also produced a visualization plan that connected each user's information needs. This involved identifying users' visualization needs, defining the types of charts to be used, and explaining the rationale for their selection. In the prototype stage, these concepts were translated into high-fidelity mock-ups. Power BI facilitated the process of creating visualization. Then, the testing stage validated the prototype. It can be done through in-depth user interviews. The dashboard design was then refined based on the feedback received.

Four-step Kimball

The system's technical architecture was designed using the Kimball four-step methodology. This methodology is useful for ensuring a robust and scalable data warehouse. The first stage is business process identification. This research focuses on the academic quality assurance (QA) evaluation cycle based on student satisfaction surveys. In this research, the level of data detail is defined as individual survey responses. Data details include each evaluation parameter related to students, lecturers, courses, and semesters. The level of data detail is determined at the lowest level to support maximum analytical flexibility.

The third stage is the identification of relevant dimensions. This stage resulted in the development of several dimension tables. The dimensions used include time (semester and academic year), lecturer profile (status and lecturer ID), study program, and question category, which are mapped to the EDOM and SERVQUAL standards. The final stage is fact identification. This process creates the fact table NilaiQADosen (LecturerQAScore). This table serves as the central database for numeric and text-based survey scores. The text can then be linked to predefined dimensions. This allows complex aggregation, longitudinal trend analysis, and multidimensional reporting.

The system was evaluated using three methods. First, task-based usability testing was conducted with internal quality assurance staff. Staff were asked to complete four scenario-based tasks. Second, a single ease question (SEQ) was administered to department heads and study program heads after each task. The SEQ uses a 7-point Likert scale (1 = very difficult, 7 = very easy), with an average score above 5.5 generally considered acceptable. In this study, the SEQ evaluation included nine respondents: four department heads and five study program heads. Third, data validity testing was conducted through a reconciliation check. The dashboard output values were compared with the source data with a tolerance of ±0.01. Performance testing was also conducted using the performance analyzer in Power BI to measure loading time.

Results and Discussion

This section presents the results of the system implementation and evaluation. The system was assessed based on four dimensions: task completion, perceived ease of use, data accuracy, and technical performance. The discussion section will examine the relationship between the results and the relevant literature.

Design Thinking Implementation

The first stage was empathy. Based on the FGD results, several issues were identified. It took the staff 3 to 4 days to clean the data from the survey system. Furthermore, there were issues with the accuracy of manually applied Excel formulas. The head of the study program also reported limited visibility of information. To date, the reports and dashboard systems produced have not detailed lecturers' work. The analysis reports generated by quality assurance also did not meet the needs for decision support. Staff needed to quickly skim through all comments to gain insight into each lecturer's performance. Based on these findings, the definition stage was conducted to clarify the issues encountered. The main issues identified were the lack of appropriate data visualization and lengthy workflow processes. At this stage, user personas were also created for internal quality assurance staff to articulate the need for a system capable of handling dynamic changes. Stakeholders needed an automated system capable of promptly transforming raw, unstructured survey data into strategic insights. Such a system was expected to eliminate the manual workload that had previously hampered decision-making. The BI system also enabled quality assurance activities to run more efficiently.

In the ideation stage, a brainstorming session was conducted using the How Might We method. Feature priorities were determined using the MoSCoW method. Prioritization was useful for establishing that an automated ETL pipeline was a must-have requirement to eliminate manual data entry. Text-based student feedback was often overlooked for processing. Even if it was processed, it was only done by skimming due to its large volume. Therefore, Sentiment Analysis was integrated using natural language processing (NLP) techniques. Furthermore, role-based access was used to ensure data security and maintain analytical focus, allowing Heads of Study Programs to access only the data relevant to their respective study programs or departments.

The prototype stage implemented the ideas into a mock-up dashboard interface that was designed with a Z-pattern reading flow to avoid visual clutter and excessive cognitive load. This arrangement was designed to align with the user's cognitive processes. This visualization provides an overview of institutional performance before exploring more detailed information on each lecturer's performance.

The testing phase involves iterative feedback to improve the dashboard's usability and visual clarity. For example, early users reported difficulty distinguishing between each category of sentiment due to the similarity of colors used. The visualization was then revised based on the feedback. The code uses color indicators. Green indicates positive sentiment, and red indicates negative sentiment. Stakeholders could also access original comments to understand the context behind the numerical scores. Based on this feedback, more detailed text tables and word clouds were implemented to complement the sentiment analysis results.

Data Modeling and ETL Implementation

This system was developed using self-service business intelligence (BI) architecture to automate the data lifecycle. The ETL process is implemented using Power Query (M Language). BI can automate the extraction of raw data from the internal quality assurance survey and transform it into a structured format suitable for visualization. The schema consists of a central fact table (Fact_NilaiQADosen) connected to several dimension tables, namely Dim_Dosen (Dosen), Dim_Prodi (Study Program), Dim_Time (Time), and Dim_Pertanyaan (Question). This structure supports flexible data analysis and reporting processes. The overall schematic design is shown in Figure 2.

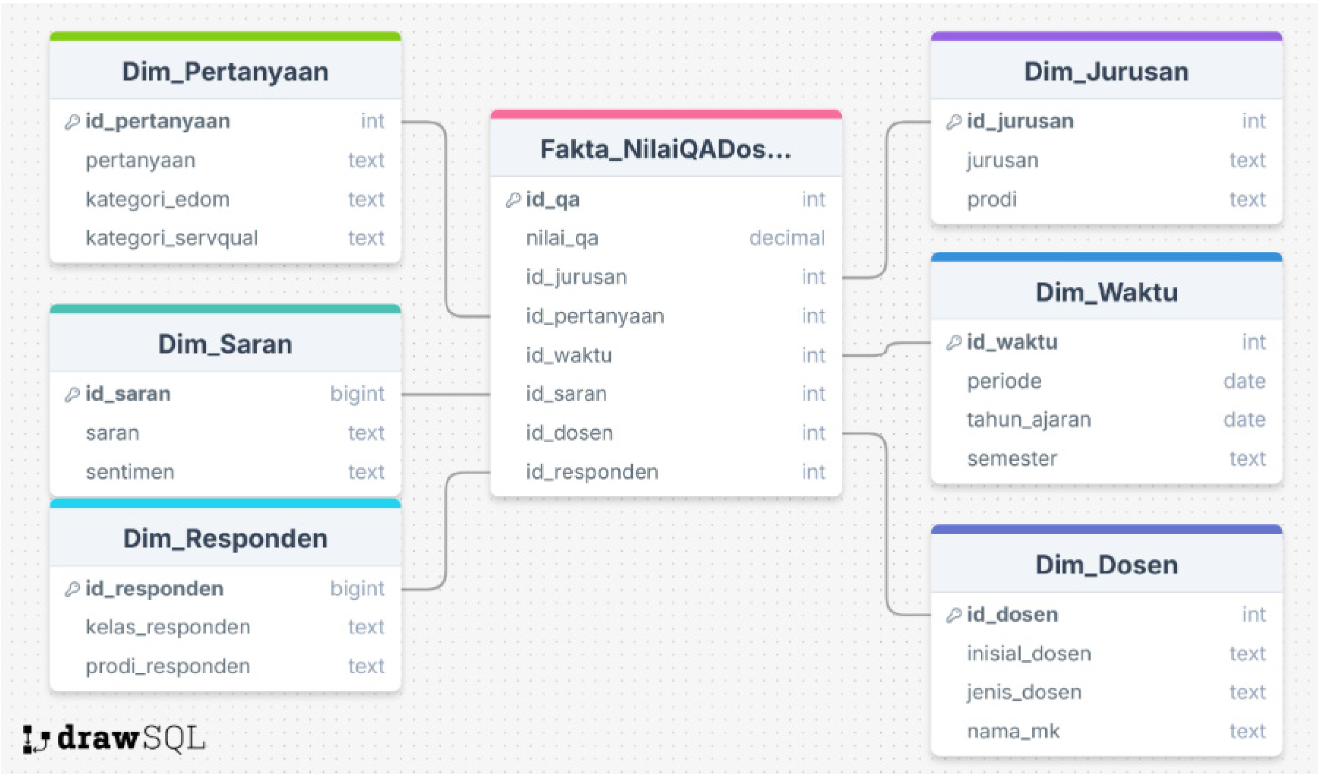

Figure 2 Star Schema

The Power Query script was designed to manage data inconsistencies (Stankovska et al., 2024) to ensure the data aligns with applicable HEIs' quality standards. Automated processes can reduce data preparation time. The scripts are used to standardize lecturer and subject names, remove duplicate data, and map dynamic survey questions. Question mapping is performed by extracting data into SERVQUAL dimensions (Tangibles, Reliability, Responsiveness, Assurance, and Empathy) and EDOM categories.

Dashboard Visualization Results

The visualization provides analytical insights for three user groups: internal quality assurance, heads of study programs, and individual lecturers.

Institutional Overview

The Overview page serves as the dashboard's main landing page. Users will get a quick overview of the overall academic quality at the institutional level. As shown in Figure 3, this page consists of several interconnected components. A line chart displays QA score trends for all three departments on a single axis, with different colors for each department, for easy comparison of trends across units. A pivot table displays the average QA score for each study program per semester, with up and down arrow icons and conditional coloring to highlight changes between periods. Two horizontal bar charts display five lecturers with the highest (in green) and the lowest (in red) QA scores. The combination of these two charts allows internal quality assurance to see gaps in lecturer quality in a single view. A notification card appears when the system detects a significant decrease in a lecturer's performance. Four KPI cards display the number of active teaching staff by category (permanent lecturers, adjunct lecturers, lab assistants, and contract lab assistants), providing an overview of the teaching staff composition. A gauge chart displays the survey completion rate for the selected period along with a comparison to the previous year, while a card visual with a mini sparkline displays the number of respondents and the percentage change compared to the previous year.

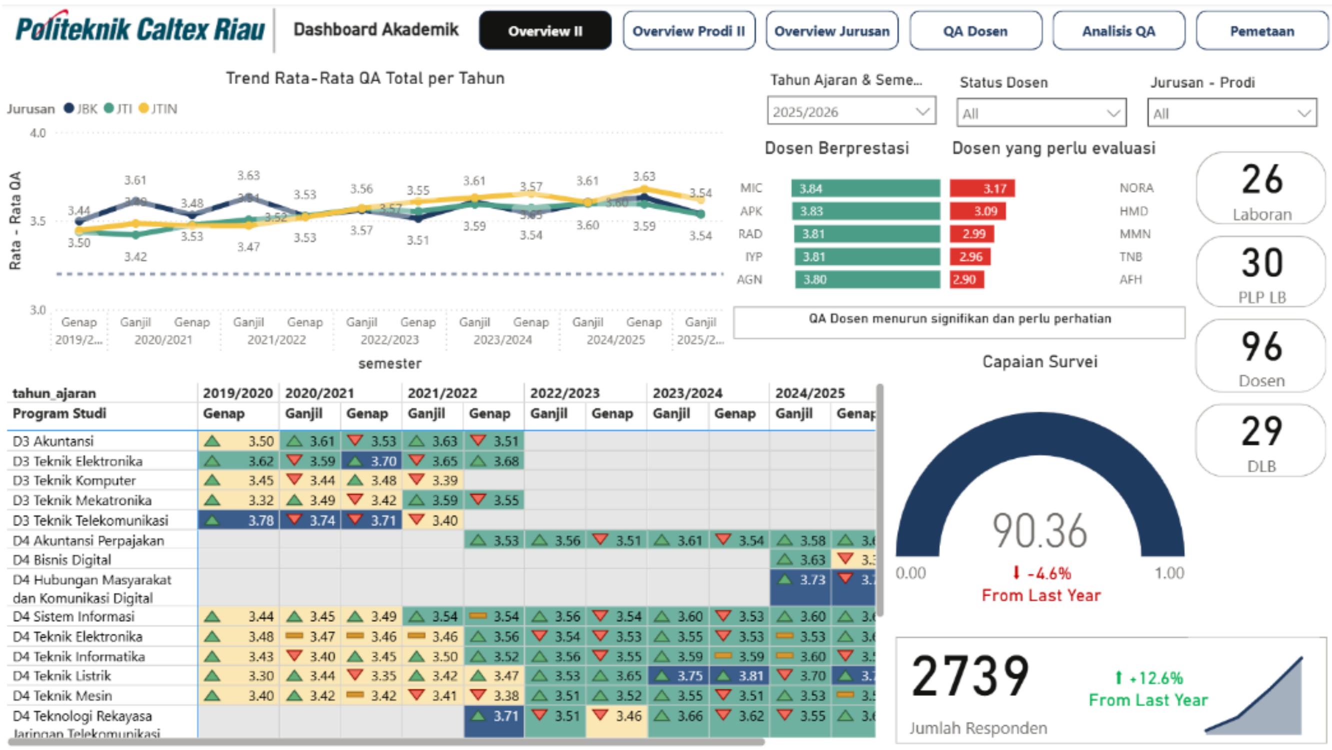

Figure 3 Institutional Overview Dashboard

Figure 3 shows the Overview page, where the multi-line trend chart makes it easy for users to see changes in QA performance across all three departments at PCR over time. Each department can be clearly distinguished through the use of different colors. The pivot table below allows Internal Quality Assurance to review all study programs simultaneously and immediately identify study programs experiencing an increase or decrease each semester through directional icons and cell coloring. The highest- and lowest-performing lecturer charts provide an immediate picture of the distribution of teaching staff quality within the institution, supporting recognition of high-achieving lecturers as well as early identification of lecturers who need mentoring. The automatic notification card adds an important proactive element. The decreasing-trend flag is automatically calculated. These components enable internal quality assurance to shift from a reactive end-of-semester data evaluation process to continuous, evidence-based quality monitoring.

Department and Study Program Analysis

The study program overview page is designed for heads of study programs and heads of departments. It provides a view that is automatically filtered based on each user's study program, as shown in Figure 4.

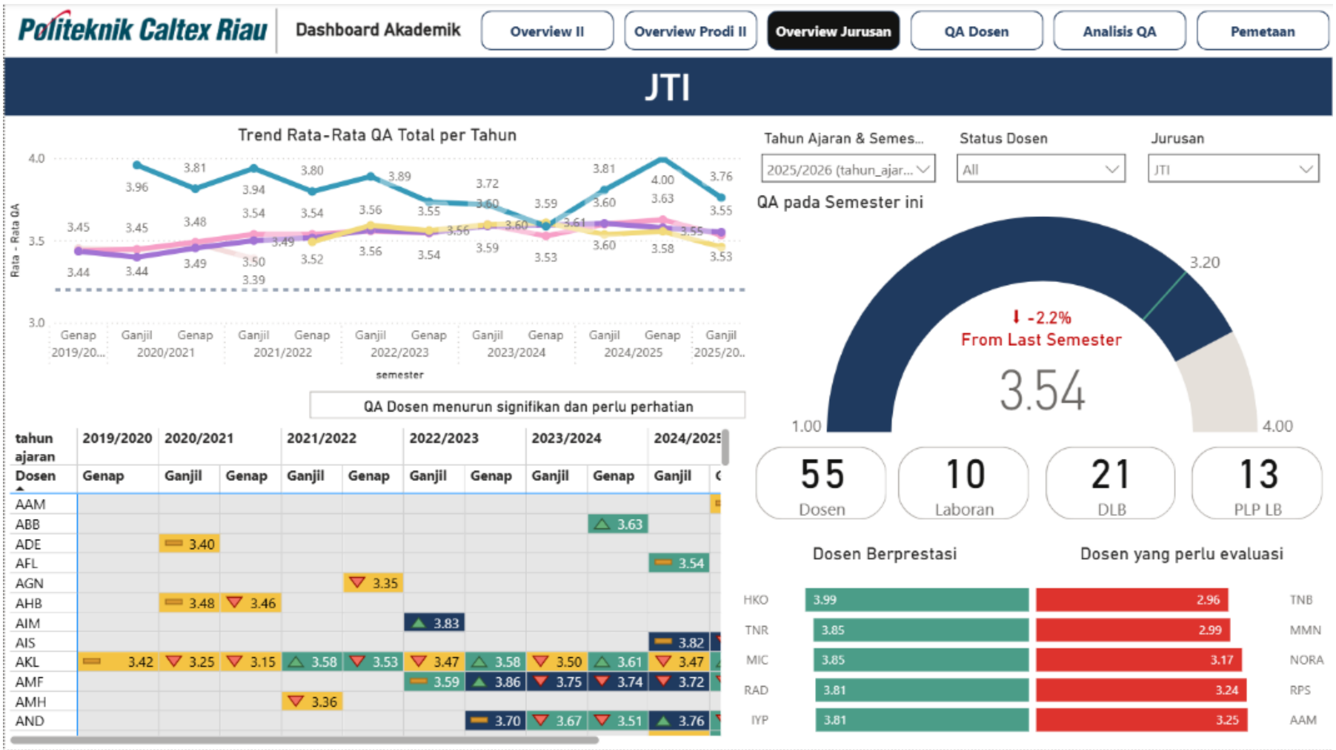

Figure 4 Department Performance Dashboard

Figure 4 shows the study program overview page. Department heads monitor quality trends between semesters. A banner displays the name of the selected study program. A line graph shows the study program's QA trend over time. A gauge graph displays the average QA score for the current semester on a scale of 0–4.00, along with a percentage change compared to the previous semester.

Four KPI cards display the number of active members within the study program. A pivot table displays all lecturers teaching in the study program, their QA scores for each semester, and a change indicator. This allows department heads to monitor the consistency of lecturers' performance over time. Two horizontal bar graphs show the top five lecturers (green) and the five lecturers with the lowest scores (red). These visuals are used to provide a quick overview of lecturer performance distribution per department.

Furthermore, a card automatically flags lecturers who show a downward trend to keep the analytical focus on decisions within the user's area of focus. The lecturer's performance chart, from the highest to the lowest, is clearly displayed.

Lecturer's Performance Analysis

The lecturer's performance dashboard is shown in Figure 5. This page is used by lecturers to evaluate their own performance. For internal quality assurance and heads of study programs, this visualization is used for monitoring and evaluation purposes. There is a detailed view of individual lecturer performance by combining quantitative performance metrics with qualitative feedback analysis. At the top left is a gauge chart displaying the lecturer's average QA score on a 0.00–4.00 scale, along with the percentage change from the previous semester. A line chart shows the QA trend across semesters. A scrollable text table displays all student comments in full. A word cloud displays the words that appear most frequently in student feedback. Next to it is a pie chart showing the proportion of positive, neutral, and negative sentiment, automatically classified using a Python-based NLP pipeline (Kastrati et al., 2021). A horizontal bar chart displays QA scores by course taught, sorted from the highest to the lowest score. Two donut charts display the distribution of scores based on the four EDOM categories and the four SERVQUAL dimensions.

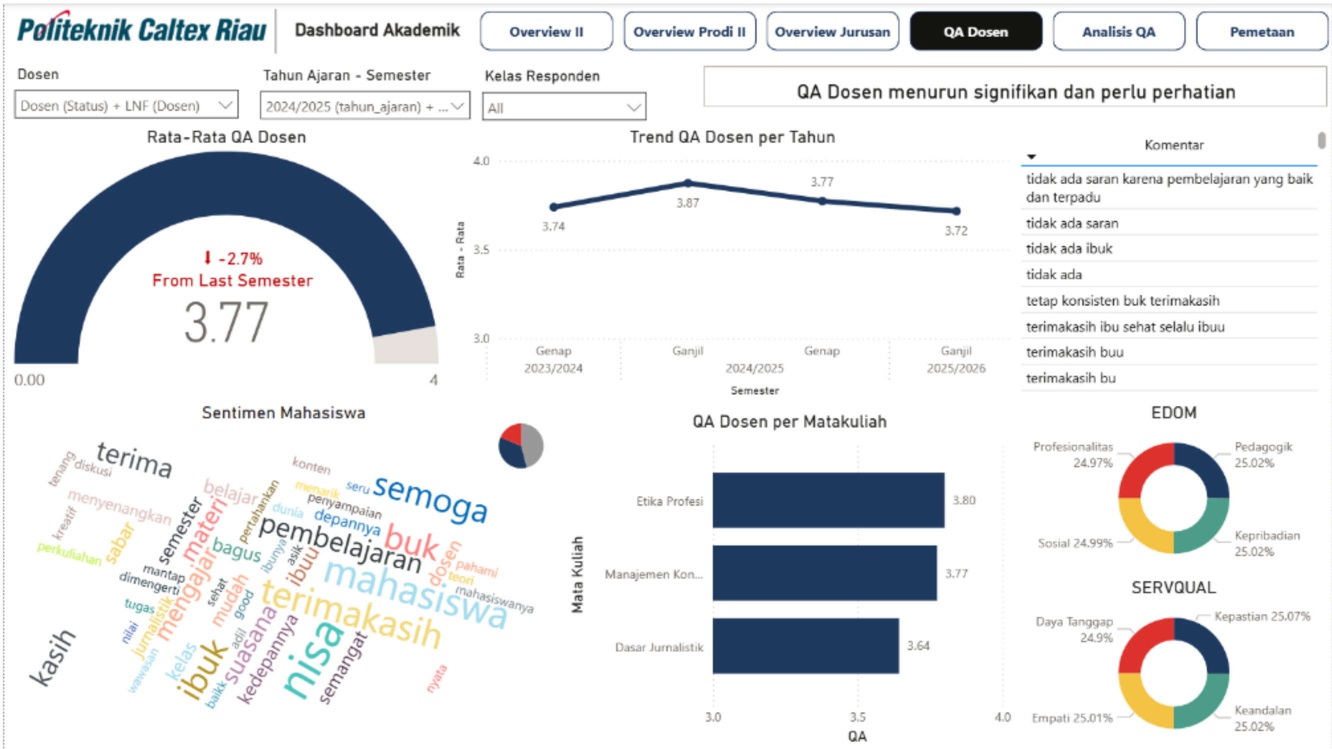

Figure 5 Individual Lecturer Dashboard

Figure 5 displays the QA page per lecturer. The gauge chart at the top shows the lecturer's position on the rating scale. The semester line chart below provides a necessary dimension for assessing score consistency. The word cloud displays the most frequently raised themes in student feedback, while the pie chart indicates the overall sentiment of comments, whether positive, neutral, or negative. This sentiment analysis can help analyze the reason for a lecturer's QA score being high or low. Course-level bar charts then show which teaching assignments performed the strongest and weakest. Donut charts for EDOM and SERVQUAL provide a clearer view of the lecturer's performance across different quality dimensions.

Question-Level Analysis

This page enables deeper diagnostics through analysis at the level of individual survey questions (Q1–Q20). As shown in Figure 6, a column chart displays the average score for each of the 20 survey questions. These results provide a quick overview of the distribution. Two horizontal bar charts directly highlight the learning aspects that received the highest and lowest ratings. A large pivot table displays each lecturer's score for each question. Internal quality assurance can compare lecturers' strengths and weaknesses. This page supports decision-making at two levels. At the institutional level, it identifies aspects of learning quality that are consistently weak across all lecturers, while at the individual level, it allows comparison of lecturers for each question.

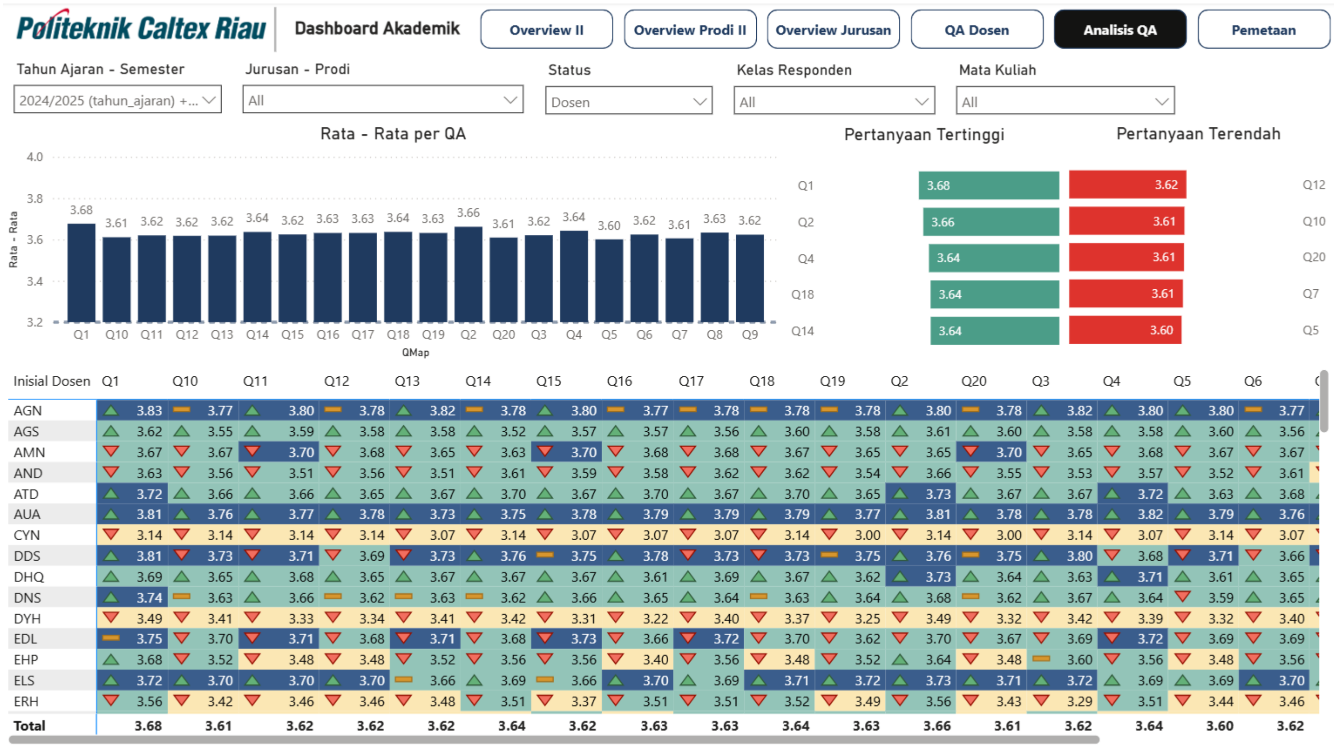

Figure 6 Question Analysis Dashboard

Figure 6 shows the question analysis dashboard page. The column chart provides a complete overview of all 20 questions. The combination of horizontal bar charts allows internal quality assurance to act on the most important findings without having to read the entire chart. The pivot table at the bottom is useful for cross-lecturer analysis. It allows identification of whether a question with a low score represents a systemic issue affecting most lecturers or is caused by only a small number of specific individuals. This distinction between systemic and individual issues represents a level of analysis previously unattainable with static reporting systems.

Quality Dimension Mapping Analysis

The quality dimension mapping page shows changes across dimensions over several academic years to allow internal quality assurance to determine whether quality improvements are sustained or whether certain competency areas remain weak. This page focuses on longitudinal trend analysis using EDOM and SERVQUAL. This page uses an area chart for each dimension: the four EDOM categories (pedagogical, professional, personality, and social) and the five SERVQUAL dimensions (reliability, responsiveness, assurance, empathy, and tangibles). Each dimension is displayed in a separate chart to make reading trends easier. The shaded area beneath the line reinforces the perception of magnitude to make it easier to identify when a dimension decreases significantly.

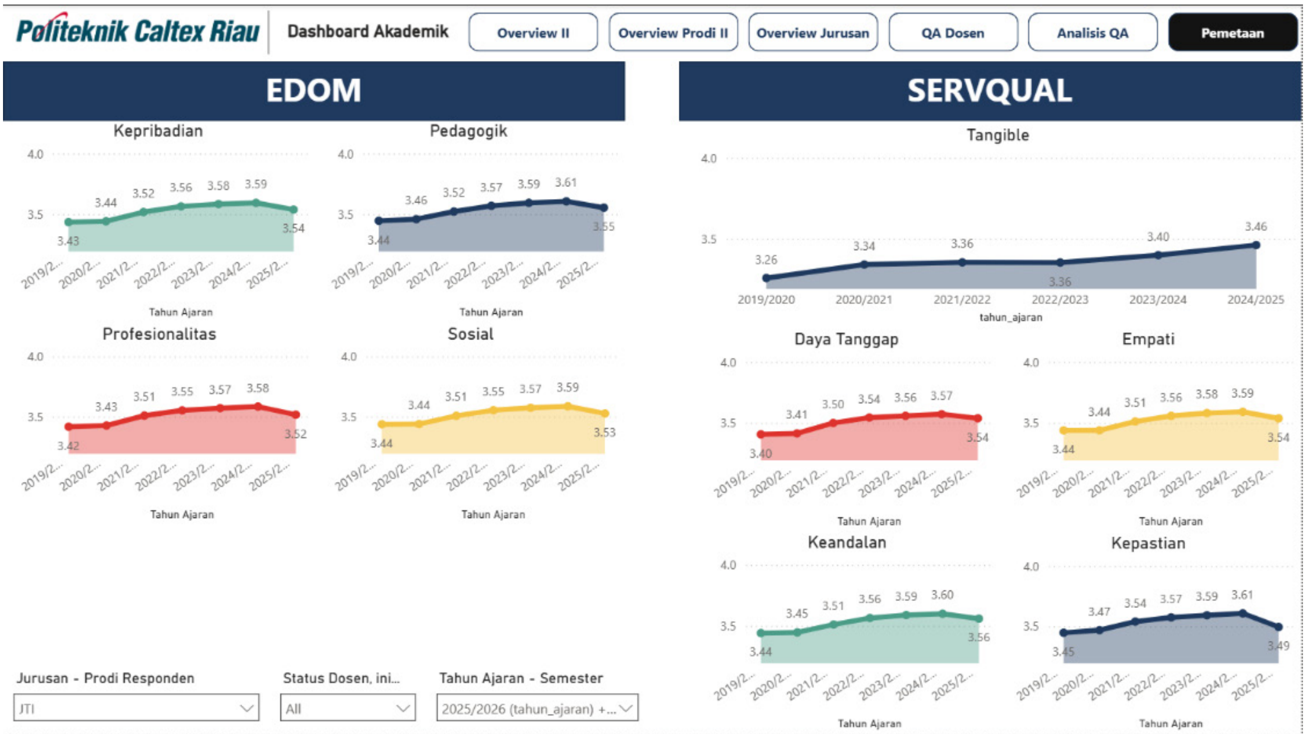

Figure 7 Dimension Mapping Dashboard

Figure 7 shows how mapping survey questions onto the EDOM-SERVQUAL framework can transform individual scores into a structured, standards-based representation of quality. This approach has high analytical value because it enables comparisons not only between study programs but also against established educational quality benchmarks. For example, if a study program achieves a high score on the EDOM pedagogical dimension but a low score on the SERVQUAL reliability and empathy dimensions, this indicates that although the delivery of learning material is good, students still feel a lack of consistency in service and lecturer attentiveness toward them. This page allows internal quality assurance to design more targeted quality improvement programs. This type of framework-based analysis cannot be obtained from raw question scores alone and provides a stronger evidentiary basis for more in-depth human resource development planning.

The transition from manual Excel-based data processing to a Power BI-based data model has significantly improved the quality assurance process at PCR. The implementation of an automated power query pipeline successfully reduced the human errors that previously frequently occurred during the manual data mapping process. By building a centralized data model within Power BI, the system creates a sole source of truth (Kimball & Ross, 2013), in which reports accessed by internal quality assurance have the same mathematical consistency as the reports viewed by each study program. This integration successfully resolved previous issues related to data inconsistency and delays in the reporting cycle. The resulting efficiency gains are highly significant. Whereas the previous manual workflow required three to four days for each reporting cycle, the automated pipeline can complete the same process in less than 20 minutes. This shows a reduction in data preparation time by approximately 99%. One of the central questions in socio-technical business intelligence research is whether digitalization can truly improve organizational transparency and accountability or whether it merely shifts existing information gaps into a different form. The findings of this research point to the former. By building a centralized data model, the system creates a verifiable and institutionally usable view of quality data that was previously scattered across various separate Excel files managed by different teams. The automated power query pipeline eliminates the manual mapping errors that made QA data less reliable, while the role-based access control mechanism ensures that all stakeholders work from the same data source.

Table I Comparison of Data Processing Workflow

Real Social Interaction	Manual Processing	Automated Processing
Data Cleaning Time	3-4 Days	< 20 Minutes
Data Integrity	High risk of data duplication and error	Automated validation
Report Flexibility	Static Dashboard	Interactive Dashboard
Sentiment Analysis	None (Manual reading)	Automated Classification
Adaptability	Manual re-mapping when questions change	Automated re-mapping logic using Power Query

The developed dashboard was evaluated using four methods: Task-based usability testing, the single ease question (SEQ), data validity testing, and system performance testing. All internal quality assurance staff completed all assigned tasks with a 100% success rate. The SEQ evaluation conducted with heads of department and heads of study programs, using a 7-point Likert scale, yielded an average score of 6.08 out of 7, which is above the 5.5 acceptance threshold and indicates a high level of ease of use.

Data validity testing achieved 100% accuracy across all reconciliation processes within a tolerance of ±0.01. The performance testing showed that all dashboard visualizations could be loaded in less than 500 milliseconds. It meets the established response time target. These results are consistent with the research of Azzahra et al. (2025). Based on that, we used a similar hybrid methodology and achieved a 30% increase in task completion rate following an iterative refinement process. It also demonstrated improvements in both technical performance and user experience. This research extends those findings by applying them specifically to the context of academic quality assurance in vocational HEIs.

Table II Comparison of Data Processing Workflow

Evaluation Method	Respondents	Result
Task-Based Usability Testing	Internal Quality Assurance staff (1 person)	100% task completion rate (4/4 tasks)
Single Ease Question (SEQ)	4 respondents (Head of Department and Head of Study Program)	Mean SEQ score = 6.08 / 7 (7-point Likert scale)
Data Validity Testing	All 43 dashboard visuals	100% pass rate (tolerance ±0.01)
Performance Testing	All 43 visuals, 6 pages	All visuals load in < 500 ms

In terms of ease of use, interactive filtering capability received the highest rating in the SEQ tasks. Respondents reported that historical performance trends could be obtained within seconds, compared to the previous process, which required users to open and search through numerous separate Excel files. This result reflects the effectiveness of the iterative design thinking process. The dashboard features were developed based on user problems. The sentiment analysis feature was introduced in response to stakeholder feedback. These refinements show that user-centered development can produce features that are functional and provide tangible value to users.

In addition to technical efficiency gains, the dashboard also altered work culture within the internal quality assurance environment. The change from manual data entry to data interpretation and analysis allows staff to focus more on extracting strategic insights. This change also highlights the importance of digital literacy training. The user can correctly interpret data visualizations and use the available information to assist in policy decision-making (Hjelle et al., 2024).

This research still has limitations. The sentiment analysis model used relies on a general lexicon and is not fully capable of capturing academic terminology. It also cannot comprehend the nuances of the local language and slang that students frequently use. The dashboard's effectiveness depends on students' timeliness in completing the survey, a behavioral factor beyond the system's control.

Conclusion

This study develops an academic quality assurance dashboard for Politeknik Caltex Riau to address a research gap that has rarely been explored in the literature: the integration of design thinking and the four-step Kimball methodology within a single BI-based QA system for a vocational HEI. From a theoretical perspective, it demonstrates that design thinking can be used to elicit user-centered requirements in BI system development. It thereby complements the technical rigor offered by the Kimball lifecycle. From a practical perspective, this study develops a functional system architecture capable of automating the entire data lifecycle, ranging from survey data extraction, and mapping to the EDOM-SERVQUAL dimension to the development of interactive visualizations evaluated through system performance measurements and usability testing using standardized instruments.

From a technical perspective, the main contribution of this research is the development of a Self-Service Business Intelligence architecture that automates the entire data lifecycle. The transition from a fragmented, Excel-based data-processing approach to a centralized Power BI-based data model resulted in a highly significant reduction in data-cleaning time. As shown in Table I, the previous manual process required three to four days for each reporting cycle, while the automated Power Query pipeline can complete the same process in less than 20 minutes. This is equivalent to a reduction of approximately 99%, calculated by comparing the average manual processing time (3.5 days, or approximately 2,800 minutes assuming standard working hours) with the automated processing time (less than 20 minutes). The automated Power Query algorithm ensures that annual changes in survey questions' order remain consistently mapped to the standardized SERVQUAL and EDOM dimensions. This allows preserving data integrity and establishes a reliable single source of truth for all stakeholders within the institution. In addition, this system improves analytical capability by integrating sentiment analysis and longitudinal trend tracking, which allows student feedback to be transformed into strategic insights that were previously hard to obtain.

From a socio-technological perspective, dashboard implementation has produced a meaningful change in how internal quality assurance and study program leadership utilize survey data. The automation of data processing activities allows staff to redirect their efforts toward analytical tasks, thereby allowing support for more informed and timely decision-making processes. This shift in work culture is significant because it extends the benefits of the system beyond operational efficiency. The findings demonstrate that a well-designed BI system can support institutional readiness for evidence-based governance. As a result, the practice of data-driven decision-making can become more deeply embedded in organizational culture, which is relevant to PCR's goal of maintaining excellent accreditation status and strengthening its competitiveness at the ASEAN level by 2031.

Despite its various contributions, this research still has limitations. The sentiment analysis model used still relies on a general-purpose lexicon and is not fully capable of capturing the nuances of academic language or student slang that are often used in feedback. In addition, the effectiveness of the system also still depends on how honest student participation is in completing the survey, which is a factor beyond the system's direct control. Therefore, future research could focus on integrating predictive analytics to forecast lecturer performance trends and identify courses at risk of quality decline much earlier, and also on refining the natural language processing (NLP) component using a dataset more specific to the higher education domain to improve the accuracy of qualitative student feedback analysis.

Acknowledgement

The authors would like to express their gratitude to PCR internal quality assurance for their support and for providing access to the necessary data. They also thank the heads of study programs and lecturers who participated in the focus group discussions and system testing phase of this research.

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