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Incorporating Learning Analytics and Business Intelligence into Higher Education E-Learning

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Abstract- Business Intelligence (BI) represents a pivotal advancement in leveraging information technology to enhance organizational performance. BI tools serve as crucial aids in decision-making processes by furnishing requisite insights. In higher education institutions, BI can contribute to leaders and managers in providing perspectives related to academics, learning, and management. Central to BI development is the meticulous gathering of requirements, a process pivotal in identifying organizational informational and knowledge needs. This involves employing various methods such as interviews, observation, and analysis, including leveraging learning analytics to discern data utility for enhanced learning processes. Various studies show that learning analytics contributes to improving the learning and education process. On the other hand, learning analytics requires activity data that is integrated, subject oriented, and time series which are aligned with the characteristics of the data warehouse (DWH) as the main component of BI. This research endeavors to develop BI utilizing academic and e-learning data, exemplified through a case study of Telkom University's Academic Systems and Learning Management Systems (LMS). This study aims to provide actionable insights into the intersection of BI and learning analytics, ultimately enhancing educational processes and organizational decision-making capabilities. By integrating learning analytics into BI development, the resultant BI systems can cater not only to current managerial demands but also anticipate future analytical needs. The implementation of the multidimensional schema was successfully executed. This process involved mapping data from the academic information system and the LMS as data sources to the data warehouse, the Extract, Transform, and Load (ETL) process, and development of the prototype. The testing on the prototype indicated that the prototype meets the intended requirements and provides valuable insights through its comprehensive reporting capabilities. This demonstrates the effectiveness of the implemented multidimensional schema, ETL process, and the overall design of the reporting dashboard.

Keywords: business intelligence, data warehouse, e-Learning, learning analytics, Learning Management Systems

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1. Introduction

Business Intelligence is one of the advanced technologies to improve organizational performance. BI tools assist organizations in providing the knowledge needed for decision making[1] [2]. BI tools consist of various components, including data warehouse (DWH) and data marts. Universities are ideal implementers of BI, given the intense competition in the admissions process [1] and in university rankings. In higher education institutions, BI can contribute to leadership and management in providing perspectives related to academics, learning, and management [3]. Several studies emphasize the importance of BI in learning, including for the analysis of the dropout phenomenon [4] and the development of quality learning [5]. In education, the greatest potential in applying BI is in e-learning. Because through e-learning, abundant data is generated and generally describes the learning process at the institution.

There are two popular approaches to BI development, the Top-Down Approach supported by Inmon and the Bottom-Up Approach supported by Kimball. The advantage of the Top-

Down approach is the availability of an integrated and flexible architecture for decision making. In this approach DWH as the backbone of BI provides designs and schematics for each data mart, so that consistency and standardization in all data marts can be maintained [6]. On the other hand, the Bottom-Up Approach is considered more suitable if the DWH development is carried out with limited time and costs. This is because data marts are developed in stages [6].

In this study, the Bottom-Up approach was chosen which was initiated by Kimball because it is in accordance with the system development process that is applied to the case study, namely in universities where system requirements are built in stages. In general, the Bottom-Up Approach consists of the following steps: Select the Business Process, declare the grain, Identify the dimension, and identify the facts. In the first stage, business processes are determined as a reference for BI development. In the process of declaring the grain, the information and knowledge needed by the organization is identified. This process can be done through interviews, observation, and analysis of opportunities for the usefulness of data with learning analytics.

At the stage of declaring the grain in general, the grain is identified only by looking at current reporting needs. Generally, this is sufficient to support managerial decision making. However, there is great potential for the data stored in the LMS. For example, current reporting needs are still related to the amount of content available and the amount of student access to that content in the LMS. This data can be processed for future decision making. These include identifying at-risk students, personalizing learning experiences, improving course content, and optimizing resource allocation.

E-learning data stored in LMS has the potential to help institutions in descriptive, predictive, and prescriptive analytics [7] as well as provide perspectives on the learning and teaching process [8][9]. The convergence of LA and BI in the context of higher education e-learning holds promise for addressing various educational challenges. By harnessing the power of data, educational institutions can foster a more responsive and adaptive learning environment, ultimately enhancing student success and institutional effectiveness. The purpose of this research is to propose an E-Learning BI framework that accommodates current knowledge needs as well as opportunities for learning analytics from the perspective of institutions, teachers, and students. In this study, the academic and LMS information system that is used as a reference is the systems implemented at Telkom University named iGracias.

2. Methods

Based on the Bottom-Up approach, designing BI (or especially DWH) consists of four steps as follows: select the business process, declare the grain, identify the dimensions, and identify the facts. Selection of business processes is carried out to decide the focus of business requirements and the analysis of available data. Meanwhile, the stage of declaring the grain determines what is presented by each row in the fact table. The grain shows the level of detail of the measure in the fact table. In this process, current knowledge requirements and future data analysis opportunities are identified and defined. At this step, it is important to confirm the organizational knowledge needs of process owners, managerial and strategic officers. In addition, data analysis opportunities can be obtained through a study of several previous studies that utilize data contained in the LMS to be analyzed using a learning analytics approach. The methodology developed in this research is shown in Figure 1. The colored block shows the main contribution of this research.

Figure 1. E-Learning BI Design Step

Defining the dimensions step is carried out after the grain is defined. Meanwhile, the identify the facts step is carried out to complement the existing grain and dimension designs. Dimension tables and fact tables then form a dimensional schema. In this study, the dimensional schema used is in the form of a star-schema which consists of one fact table surrounded by several dimension tables related to the schema. So that the number of dimensional schemas will be as many as the fact tables.

3. Result

This section discusses the results of each stage of BI E-Learning development carried out in this study.

1. Data Source Analysis

Academic Information System is a system used by educational institutions to manage and manage academic data such as student data, class schedules, grades, student attendance data, and so on. The system has a very high level of urgency to facilitate administrative processes and decision-making processes by academics. In Telkom University, the platform used is called iGracias. It has integrated academic features including 28 academic application modules, 34 non-academic modules, and 10 strategic modules in 1 platform. This application is also supported by an RFID-based student and lecturer attendance module, a mobile platform called My Tel-U and payment gateway-based multi-channel payments.

Telkom University uses a web-based Learning Management System (LMS) platform CeLOE. CeLOE LMS is a platform used to facilitate online teaching and learning activities, such as providing lecture materials, assignments, online exams, discussions between students and lecturers, and monitoring student learning progress. CeLOE LMS has features that facilitate the management of online learning, such as integration with Telkom University, setting study schedules and activities, managing assignments, managing grades, and managing online classes. CeLOE LMS uses the latest version of Moodle and is customized with additional features needed by Telkom University. The modifications made include integration with other academic systems, such as Academic Information Systems and financial systems, and the addition of special features such as evaluation and project-based learning features. The use of Moodle as an LMS platform was chosen for several reasons, such as: open source, flexible, and familiar to users in universities and other educational institutions around the world.

2. Selecting Business Process

To ensure the effective integration of LA and BI into e-learning systems, it is crucial to understand the specific needs and business processes of educational institutions. At this step, interviews were conducted. Interviews were conducted by inviting management, e-learning administrators, and the head of study programs. These interviews, along with an analysis of source data, identified the critical business processes to be covered in the BI e-learning system: course activities, assessments, students' activities, and students' assessments. This need was identified based on the data requirements for reporting on management performance achievements, institutional annual reports, and operational teaching activities at the program study and faculty levels. This business processes are supported by two data sources, namely iGracias as an Academic Information System and CeLOE LMS as an e-learning platform. iGracias supplies data related to learning plans, courses held, course lecturers, and students participating in courses. Meanwhile, CeLOE LMS supplies data related to learning activities and content provided by teachers, access made by students, and assessments that take place in the LMS.

3. Declaring the Grain

At this step, an analysis of the results of interviews and literature studies of various studies in the field of learning analytics that utilize e-learning data, especially LMS, is carried out. From the interviews it was found that the duties of the interviewee related to the LMS were to check course attendance and activities, as well as to check the achievement of faculty management contracts and study programs related to lecture content. The menu that is most often used in the LMS is the attendance report and course activity. The current reporting needs are details of lecturer activities and details of student activities that can be accessed by lecturers and study programs. Opportunities for data analysis can be obtained through a study of several previous studies that utilize the data contained in the LMS to be analyzed using a learning analytics approach.

Learning analytics in recent research has been proven to help institutions and lecturers improve the learning process with data-based decision making and treatment [10][11]. It can be designed to give a clearer and more comprehensive view related to student's struggles, achievements, and learning pattern [12]. Previous scholars applied learning analytics in modelling students such as: analyzing students' pace, effort, and progress [13][14][15][16], recognizing student behaviour [17], learning patterns[18][12], and students at risk detection [19]. We conducted an analysis regarding the potential for further use of the data stored in the LMS. This is done in addition to the results of interviews with management and decision makers. The analysis was carried out by expanding grain identification with previous learning analytics research that utilized similar data.

From the results of the selecting business process stages, it was determined that the main business processes taken were course activities, assessments, students' activities, and students' assessments. Course activities explain the activities provided at the LMS for each subject, while assessments show the form of assessment carried out by the lecturer in each subject. Meanwhile student activities explain the log of learning activities from students in accordance with the activities provided by the course. Students' assessment can be divided into two types, namely quizzes and assignments. Student activity on the quiz can be seen from the attempts they make. While the assignment assessment is carried out every time student makes a submission.

The number of activities provided according to activity modules per section based on subject, equipped with information on teaching lecturers, study programs, faculties, and semester information. This data requirement is based on the points in the management contract. The number of assessments scheduled per section is based on subject, equipped with information on lecturers, study programs, faculties, types of assessments and semester descriptions. Like course activities, data related to the number of assessments provided are also based on points in the institutional management contract and the managerial needs of the study program. Grains related to provided course activities and scheduled assessments are generally identified from current managerial reporting needs. This is different with grains related to the activities carried out by students and the process of fulfilling assessments submitted by students which are more based on potential data analysis in the future.

Frequency of access and actions taken by students for each learning activity provided per subject section, accompanied by information on study programs, faculties, module descriptions and semester descriptions. According to the head of study programs, reporting on student activities will be very much helping them to evaluate the learning process. In addition, several studies have used student activity data for various analyses, including using student interaction data [20] [21], learning activities [22], activities in discussion forums [23][24]. These studies use activity logs both on other e-learning platforms and specifically process log data on Moodle [25].

Grade, duration, time information for each quiz attempt conducted by students, accompanied by section, course, quiz module, study program, faculties, and semester information. Assessment student data in the form of quizzes or tests has been used by many previous studies [26]. For example, analysing pre-test and post-test scores to provide personalized learning [27]. This data has also been a need for lecturers, study programs and faculties in measuring the achievement of student competencies.

Grades and time information for each submission made by students to module assignments are accompanied by information on sections, courses, study programs, faculties, and semester descriptions. Like the data from the assessment quiz, data related to the submission of student assignments is also one of the tools in measuring student competency. In addition to grades, student assignments are also seen from the side of their fulfilment. Among other things, to detect student failure [19] and become the basis for providing learning design [28].

4. Dimensions and Facts Identification

The next step is to identify the dimensions according to the fact table based on the level of detail that has been described previously. The fact table consists of a foreign key from the dimension table that surrounds it and the measure variable that has been described previously. While the dimension table consists of variables that describe these dimensions according to the data stored in the source table used. The bus matrix in Table 1 is a general description of the DWH that will be made. The bus matrix describes the mapping of candidate fact tables and dimension tables. From the results of the stages of declaring the grain, the dimension tables were identified as described in Table 2.

Table 1. Bus Matrix

Fact Tables	Dimension Tables												
	Courses	**Sections**	**StudyPrograms**	**Faculties**	**Students**	**Lecturers**	**Semesters**	**Assessments**	**Quiz**	**Assignment**	**Activities**	**Modules**	**Actions**
CourseActivities	X	X	X	X		X	X					X	
StudentActivities	X	X	X	X	X		X				X	X	X
QuizAttempt	X	X	X	X	X		X	X	X				
AssignmentSubmission	X	X	X	X	X		X	X		X			
CourseAssessment	X	X	X	X		X	X	X					

Table 2. Dimension Tables Description

Dimension Tables	Description	Attributes
Courses	Class Course Example: Modeling Database 01	CourseID(key) CourseName CourseCode CourseNameWithClass
Sections	Sections yang terdapat pada setiap Course Class Example: Section 1, Section 2, etc	SectionID(key) SectionName
StudyPrograms	Study Program yang mengampu Course Example: Computer Science	StudyProgramID(key) StudyProgramName
Faculties	Faculty dari Study Program Example: School of Computing	FacultyID(key) FacultyName
Students	Student Example: 12345- Diane Ross	StudentID(key) StudentName Username
Lecturers	Lecturer Example: JK – John Kimball	LecturerCode(key) LecturerName Username
Semesters	Semester and Academic Year Example: Even – 2022/2023	SemesterID(key) SemesterName AcademicYear
Assessments	Assessments Module Example: Quiz/Assignment	AssessmentType(key) AssessmentDescription
Quiz	Quiz arranged by lecturer. Example: SQL Quiz	QuizID(key) QuizTitle TimeOpening TimeClosing MaxDuration MaxAttempt MaxGrade LastModified
Assignment	Assignment arranged by lecturer. Example: Database Implementation Project	AssignmentID(key) AssignmentTittle TimeOpening TimeClosing Grouping LastModified
Activities	Activity or resource added by lecturer Example: Lecturer Note: ER Model	ActivityID(key) ActivityName LastModified
Modules	Type of Activity Module Example: Forum Discussion, Chat, etc	ModuleType(key) ModuleDescription
Actions	Action taken by students related to available activities. Example: Add discussion, View Resource, Reply Messages, etc	ActionName(key) ActionDescription

4. Discussion

1. Multidimensional Model

The results of the detailed analysis can be seen in Figure 2-6. The Course Activities Fact Table shows the number of activities provided according to the activity module per section based on the course. While the need for data assessment which is scheduled per section based on the course is outlined in the CourseAssessments fact table. Student Activities covers the need for access data and actions taken by students for each learning activity. Data related to quizzes done by students are detailed in the QuizAttempts fact table. Meanwhile the Fact table Assignment Submission includes information related to student assignments.

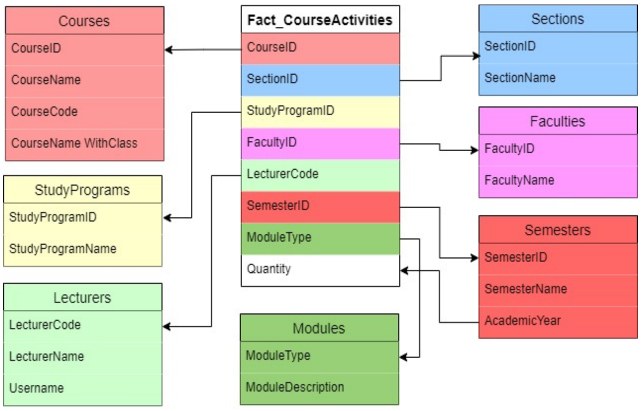


Figure 2. Star Schema for Fact_CourseActivities

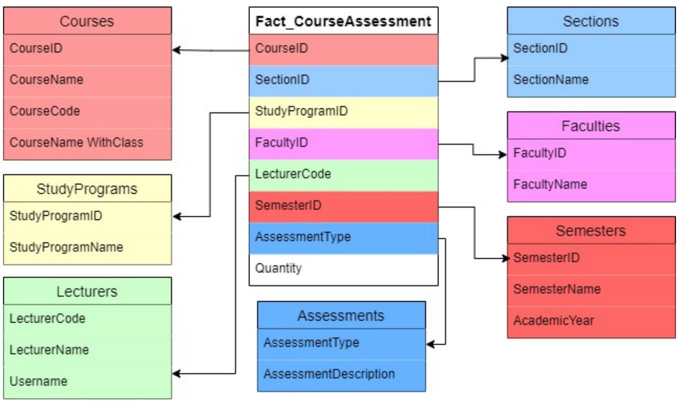


Figure 3. Star Schema for Fact_CourseAssessment

2. Dashboard Prototype

The multidimensional schema is then implemented in the data warehouse. This implementation also includes the process of mapping data from the academic information system and LMS as a data source to the data warehouse. This research continued with the Extract, Transform, and Load (ETL) process and development of the reporting dashboard prototype. Figure 7 depicted a sample of reports generated on the dashboard. The graphic version of reports is shown in Figure 8.

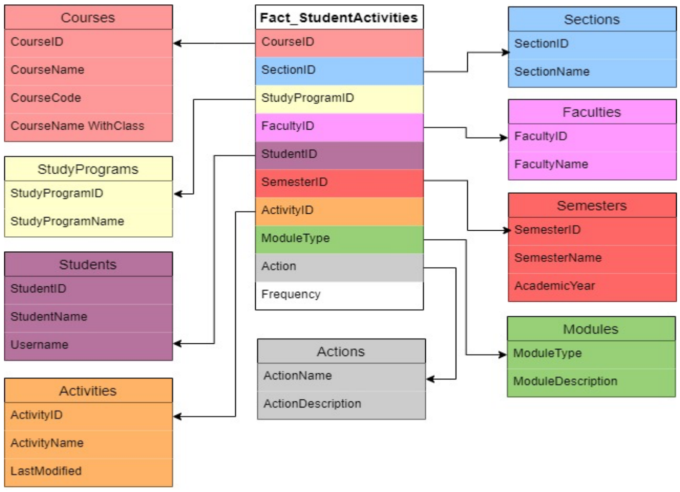


Figure 4. Star Schema for Fact_StudentActivities

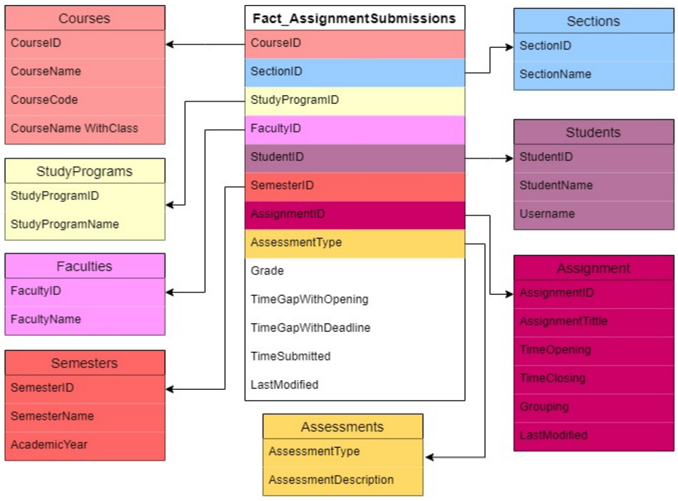


Figure 5. Star Schema for Fact_AssignmentSubmissions

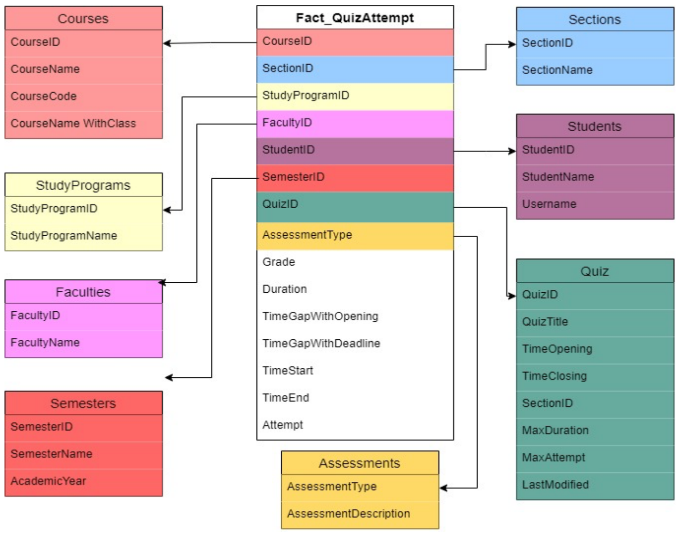
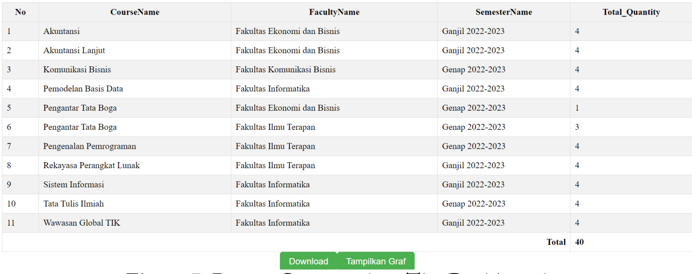


Figure 6. Star Schema for Fact_QuizAttempt



No	CourseName	FacultyName	SemesterName	Total_Quantity
1	Akuntansi	Fakultas Ekonomi dan Bisnis	Ganjil 2022-2023	4
2	Akuntansi Lanjut	Fakultas Ekonomi dan Bisnis	Ganjil 2022-2023	4
3	Komunikasi Bisnis	Fakultas Komunikasi Bisnis	Genap 2022-2023	4
4	Pemodelan Basis Data	Fakultas Informatika	Ganjil 2022-2023	4
5	Pengantar Tata Boga	Fakultas Ekonomi dan Bisnis	Genap 2022-2023	1
6	Pengantar Tata Boga	Fakultas Ilmu Terapan	Genap 2022-2023	3
7	Pengenalan Pemrograman	Fakultas Ilmu Terapan	Genap 2022-2023	4
8	Rekayasa Perangkat Lunak	Fakultas Ilmu Terapan	Ganjil 2022-2023	4
9	Sistem Informasi	Fakultas Informatika	Ganjil 2022-2023	4
10	Tata Tulis Ilmiah	Fakultas Informatika	Genap 2022-2023	4
11	Wawasan Global TIK	Fakultas Informatika	Ganjil 2022-2023	4
			Total	40

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Figure 7. Report Generated on The Dashboard

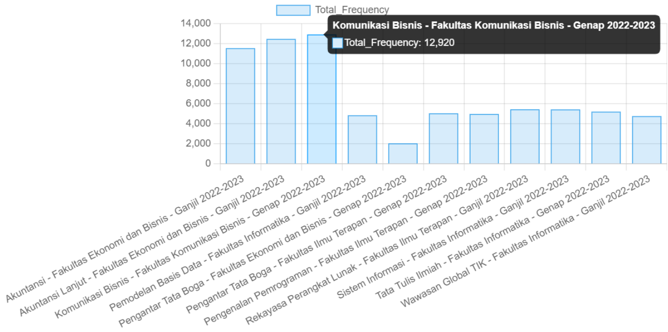

Figure 8. Graphic Report Generated on The Dashboard

The prototype then goes through testing to ensure that the dashboard being developed meets the defined requirements. The testing was conducted to five reports named after the fact defined on the declaring the grain step. To each report, we prepared some test scenarios and test cases. We invited testers to conduct testing on reports generated on the prototype dashboard. Table 3 shows a snapshot of the test items and their results. The prototype passed the given test scenarios.

Even though multidimensional data can be implemented, and a prototype successfully developed, this research still has opportunities for improvements. The testing phase was only conducted at the functionality level. In addition, the testing was carried out by testers, not by process owners or decision makers. This research will continue with testing the usability of the dashboard application and calculating the performance of the ETL process. Usability testing will ensure that the dashboard application meets user needs and provides an intuitive and effective user experience. Performance calculations will ensure the ETL process is efficient and scalable.

5. Conclusion

BI tools assist organizations in providing the knowledge needed in decision making. In tertiary institutions, BI can contribute to leaders and management in providing perspectives related to academics, learning, and management. In learning, the greatest potential in applying BI is in e-learning. Because through e-learning, abundant data is generated and generally describes the learning process at the institution.

The Bottom-Up Approach as a BI development consists of the following steps: namely: Select the Business Process, declare the grain, Identify the dimension, and identify the facts. In the process of declaring the grain, the information and knowledge needed by the organization is identified. This process can be done through interviews, observation, and analysis of opportunities for the usefulness of data with Learning Analytics. E-learning data stored in Learning Management Systems (LMS) has the potential to assist institutions in descriptive, predictive, and prescriptive analytics as well as providing perspectives on the learning and teaching process.

Table 3. Snippets of The Test Scenarios on CourseActivities Report

Test Scenario	Test Case	Expected Result	Result
…	…	…	…
Ensure the report returns the correct results for a typical set of data.	courseactivities report contains records for multiple courses, faculties, and semesters. Filter faculties: 'Fakultas Ilmu Terapan'	The report shows the correct course names, faculty name (only 'Fakultas Ilmu Terapan'), semester names, and the total quantity of e-learning activities for each course and semester combination.	PASS
Ensure the report returns the correct results for a typical set of data in graphic	courseactivities report contains records for multiple courses, faculties, and semesters. Filter faculties: 'Fakultas Ilmu Terapan' click 'Shows Graphic' button	The report shows the graphic of correct course names, faculty name (only 'Fakultas Ilmu Terapan'), semester names, and the total quantity of e-learning activities for each course and semester combination.	PASS
Verify the report handles multiple semesters correctly.	Records in courseactivities spanning multiple semesters for the same and different courses.	The report returns the correct total quantities grouped by course name and semester name	PASS
Verify the report handles multiple semesters correctly.	Records in courseactivities spanning multiple semesters for the same and different courses. Click 'Show Graphic' button	The report shows the graphic of correct total quantities grouped by course name and semester name	PASS
…	…	…	…

This research proposes a methodology for the development of BI E-Learning that accommodates current knowledge needs as well as opportunities for learning analytics from the perspective of institutions, lecturers, and students. In this study, the academic information system and LMS that is used as a reference is the system implemented at Telkom University named iGracias and CeLOE. The implementation of the multidimensional schema in the data warehouse was successfully carried out. This included the crucial process of mapping data from the academic information system and the Learning Management System (LMS) to the data warehouse. Following this, the research progressed with the Extract, Transform, and Load (ETL) process, which facilitated the transfer and transformation of data.

The development of the reporting dashboard prototype was a key milestone in this study. To ensure the dashboard met the defined requirements, extensive testing was performed on the reports. Test scenarios and test cases were meticulously prepared for each report. Testers were invited to rigorously test the reports generated by the prototype dashboard. The positive outcome of the testing phase indicates that the prototype is robust and reliable, fulfilling the intended requirements and providing valuable insights through its reporting capabilities.

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