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Article

Design of a Kimball-Based Data Warehouse for E-Learning Monitoring and Accreditation Reporting

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Abstract: E-learning platforms record course delivery, learning materials, assessment activities, and student interactions, but many higher education institutions still prepare e-learning monitoring and accreditation reporting by querying operational databases manually. This practice may limit historical analysis, indicator consistency, and reporting reuse under flexible academic service conditions. This study proposes a domain-specific Kimball-based dimensional data warehouse model for accreditation-oriented e-learning reporting. The method analyzes reporting requirements, characterizes generic LMS data sources, prepares a staging and ETL workflow, defines slowly changing dimension policies, declares formal fact grains, constructs star schemas, and evaluates reporting scenarios. Three business processes are modeled: teaching delivery, assessment records, and activity logs. The result is a reporting-oriented schema consisting of three fact tables and eleven dimension tables, supported by representative pseudo-DDL, an example accreditation monitoring query, and a limited proof-of-concept evaluation using synthetic LMS-like records. The evaluation indicates that the reference schema represents selected structured indicators for active course monitoring, learning material availability, assessment evidence, and student participation. It also reports limited ETL and query feasibility metrics and provides dashboard prototype mapping with review criteria, while full accreditation evidence remains partially covered because qualitative documents require integration with document management metadata.

Keywords: data warehouse; dimensional modeling; Kimball approach; e-learning; accreditation reporting; learning analytics; flexible academic services.

1. Introduction

E-learning platforms have become an essential part of higher education because they are used for course delivery, learning material distribution, assessment management, academic communication, and student participation monitoring. In the post-pandemic era, the role of e-learning is no longer limited to emergency remote learning. It has become part of the digital academic infrastructure used in flexible and data-informed higher education services.

The need for reliable e-learning data has become more relevant as higher education institutions face new operational challenges. In Indonesia, the Ministry of Higher Education, Science, and Technology issued Circular Letter Number 2 of 2026 concerning the adjustment of work arrangements and the adjustment of academic activities in higher education [1, 2]. This policy encourages flexible work arrangements, proportional distance learning, and the optimization of digital platforms while maintaining learning quality and academic service effectiveness [3, 4]. Therefore, universities are encouraged to strengthen digital academic platforms so that academic activities, mobility adjustments, learning outcomes, and institutional services can be monitored more systematically.

In this context, e-learning platforms play an important role because lecturers and students may rely more on digital learning environments when flexible academic services or proportional distance learning mechanisms are implemented. Activities such as uploading learning materials, conducting online assessments, recording student participation, monitoring course activities, and preparing academic reports become increasingly dependent on e-learning systems. As a result, e-learning data are not only useful for teaching and learning activities but also for academic monitoring, institutional quality assurance, and accreditation reporting.

In practice, the use of e-learning as a learning medium is often monitored through indicators such as the number of active courses, uploaded learning materials, assessment activities, lecturer participation, and student activity logs. However, the reporting process is commonly performed manually by accessing the e-learning operational database and preparing reports separately. Such a process is time-consuming, prone to inconsistency, and difficult to reuse for historical or multidimensional analysis. This condition may become more challenging when institutions are required to monitor digital learning activities regularly and prepare evidence-based reports for internal evaluation and accreditation.

Business intelligence can help institutions transform raw operational data into useful information for decision making. A data warehouse is a plausible approach for this purpose because it integrates data from operational systems into a historical, subject-oriented, and analysis-ready repository. In the educational domain, a data warehouse may support academic monitoring, accreditation reporting, dashboard development, and learning analytics. Nevertheless, the design of a data warehouse for e-learning monitoring requires a clear mapping between institutional reporting needs and dimensional data structures.

Recent studies suggest that e-learning data, learning analytics, business intelligence, and data warehouse technologies are increasingly important in higher education. Learning management systems generate large volumes of activity data that can be used for descriptive, predictive, and prescriptive analytics [13, 18, 20]. Learning analytics dashboards have also been widely studied as tools for helping students, lecturers, and institutional stakeholders understand learning processes and inform decision making [14, 15, 16, 17]. In addition, recent research has emphasized the role of data warehouses, academic data platforms, and business intelligence in educational evaluation, multidimensional analysis, and institutional decision support [23, 22].

However, several limitations can still be identified from previous studies. First, many learning analytics studies focus on dashboard visualization, prediction, or student performance analysis, but do not clearly describe the underlying dimensional data warehouse structure required to organize e-learning data. Second, several educational data warehouse studies discuss institutional or academic data integration in general, but do not explicitly map e-learning business processes into fact tables, dimension tables, and fact table grains. Third, studies related to accreditation reporting often emphasize information system development or reporting output, whereas the analytical data model that connects teaching activities, assessment records, and student activity logs is not sufficiently detailed. Therefore, a dimensional data warehouse model that explicitly connects e-learning activities, academic monitoring indicators, flexible academic service conditions, and accreditation-related reporting needs remains a relevant design problem.

This study does not claim to introduce a new data warehouse methodology or to demonstrate production-level performance improvement. Its contribution is the formalization of a reproducible dimensional modeling artifact for structured LMS-derived accreditation evidence. The proposed artifact makes explicit how accreditation-oriented reporting requirements are translated into indicators, business processes, fact grains, measures, conformed dimensions, reference schema components, and validation scenarios. The contribution is therefore methodological in the sense of making the modeling decisions traceable and reusable, rather than proposing a new data warehousing technique. The specific contributions are as follows:

1. a formal requirement-indicator-grain-schema mapping that links structured accreditation reporting needs to LMS-derived teaching delivery, assessment, and activity-log evidence;
2. explicit fact-grain definitions for the three reporting processes, including their representative measures and aggregation constraints;
3. a reproducible reference schema containing representative primary keys, foreign keys, attributes, measures, and query scenarios for implementing the proposed model in comparable institutional settings;
4. a staging, ETL, and slowly changing dimension specification that explains how LMS operational data can be transformed into reporting-ready fact tables;
5. a validation and proof-of-concept evaluation matrix that documents coverage criteria, ETL metrics, query metrics, dashboard review criteria, assumptions, and limitations for selected monitoring and accreditation evidence scenarios.

The resulting model should be read as a reusable schema blueprint and validation artifact for institutional business intelligence development. Its scope includes dimensional modeling, staging and ETL specification, limited proof-of-concept loading and query checks using synthetic LMS-like records, and dashboard prototype mapping. Production-scale deployment, full stakeholder usability testing, and predictive learning analytics remain outside the claims of this paper.

1.1. Data Warehouse in Higher Education

A data warehouse is a repository designed for analysis and decision making. Unlike an operational database, which is optimized for daily transactions, a data warehouse is optimized for querying, reporting, and historical analysis. A data warehouse is generally characterized as subject-oriented, integrated, non-volatile, and time-variant. These characteristics make it applicable to academic and e-learning data that need to be analyzed across time, study programs, courses, lecturers, and students [5, 6].

In higher education, data warehouse technology may support institutional performance monitoring, academic reporting, and quality assurance. Educational institutions usually store data in several operational systems, such as academic information systems, learning management systems, student information systems, and assessment platforms. Without an integrated analytical repository, generating reports from these systems may become inefficient and inconsistent. Therefore, a data warehouse may act as a centralized analytical layer that transforms operational data into useful information for management and decision making [7, 8, 9, 10, 11, 12].

1.2. E-Learning, Flexible Academic Services, and Monitoring

E-learning systems record various user activities, including course access, material downloads, assignment submission, quiz participation, discussion activity, and login history. These records can be used to monitor learning activities and identify patterns of student participation. In the context of flexible academic services, e-learning data become relevant evidence for examining whether teaching, assessment, and student engagement remain measurable when academic activities are partly conducted through digital platforms.

The implementation of flexible work arrangements and proportional distance learning requires universities to maintain reliable academic monitoring mechanisms. When lecturers and students interact through e-learning platforms, institutional stakeholders need structured data to evaluate course delivery, learning material availability, assessment completeness, and student participation. Therefore, e-learning data should not be treated only as operational records but also as analytical resources for academic quality assurance and accreditation reporting.

Recent studies on e-learning and online education show that digital learning platforms may generate useful data for learning analytics and decision support [19, 21, 24, 25]. However, the analytical use of e-learning data depends on the availability of structured and reliable data models. If reporting is performed directly from operational databases, the process may depend heavily on technical staff and may not support standardized institutional indicators. Therefore, a dimensional data model is needed to organize e-learning data into measurable facts and descriptive dimensions.

1.3. Dimensional Modeling and Kimball Approach

Dimensional modeling organizes data into fact tables and dimension tables. A fact table stores measurable events or numerical indicators, whereas a dimension table stores descriptive attributes that provide context to the facts. In a star schema, one fact table is placed at the center and connected to several dimension tables. This structure is commonly used to simplify query formulation and organize multidimensional analysis.

The Kimball approach adopts a bottom-up strategy in data warehouse development. Instead of building a single enterprise-wide data warehouse at once, the process begins with data marts for selected business processes. This approach is compatible with educational institutions because reporting needs can be developed incrementally based on priority areas, such as teaching activities, assessment processes, and student activity logs.

1.4. Research Gap and Contributions

Based on the reviewed literature, data warehouse, business intelligence, and learning analytics have been widely discussed in higher education. Recent studies have discussed the potential of LMS data for learning analytics [13, 18], the importance of dashboards for supporting learning and institutional decision making [14, 15, 16, 17], and the relevance of academic data platforms for educational evaluation and digital transformation in higher education [23, 22, 20]. These studies indicate growing interest in data-driven systems for monitoring, reporting, and decision making in higher education.

Table 1. Related-work positioning and modeling gap.

Research Stream	Typical Focus	Common Limitations for This Problem	Position of This Study
Generic academic data warehouses	Institutional data integration, academic reporting, and multidimensional analysis.	Often model broad academic entities without formalizing LMS-derived accreditation evidence grain.	Formalizes teaching, assessment, and activity-log grains for structured e-learning evidence.
LMS analytics studies	Dashboards, prediction, learner engagement, and intervention support.	Frequently emphasize analytical outputs without specifying reusable reporting-oriented dimensional schemas.	Specifies a reference schema intended to organize LMS records for monitoring and accreditation-oriented reporting.
Accreditation information systems	Evidence collection, document management, and institutional reporting workflows.	Often focus on application features or document workflows rather than fact-grain and measure semantics.	Maps structured accreditation evidence needs to fact tables, measures, dimensions, and query scenarios.

Nevertheless, the existing literature still leaves several gaps. First, many learning analytics studies focus on the analytical output, such as dashboards, prediction, or intervention, but provide limited explanation of the dimensional data model used to prepare LMS data for analysis. Second, several educational data warehouse studies discuss data integration and evaluation in general, but do not provide a detailed mapping between e-learning business processes and fact-dimension structures. Third, accreditation-related reporting requires consistent and traceable indicators, but previous studies rarely explain how teaching activities, assessment activities, and student activity logs can be separated into different fact tables with explicit grains. Fourth, recent policies encouraging flexible academic services and proportional distance learning increase the need for structured e-learning monitoring, but the relationship between such policy context and analytical data warehouse design remains underexplored.

This study responds to these gaps by proposing a Kimball-based dimensional model that explicitly defines business processes, fact table grains, fact tables, dimension tables, a bus matrix, reporting-need mapping, analytical report examples, and star schemas for e-learning activity monitoring and accreditation reporting. Therefore, the proposed model is positioned not merely as a general data warehouse design, but as a structured analytical schema for organizing e-learning operational records into institutional reporting indicators.

Table 1 summarizes the methodological gap examined by this study. The comparison is not intended to claim superiority over prior work; rather, it clarifies the specific modeling scope of the proposed artifact.

2. Materials and Methods

This study applies a design science-oriented data engineering procedure to construct and assess a Kimball-based dimensional model for e-learning monitoring and accreditation reporting. The methodology treats the data warehouse schema as the artifact and examines it through requirement coverage, query scenario validation, and comparison against direct operational reporting. The workflow is shown in Figure 1. Each step defines its input, process, and output to make the modeling procedure easier to reproduce and adapt by other institutions with comparable e-learning data sources.

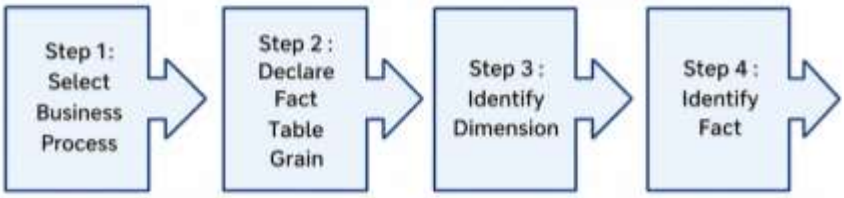

Figure 1. Kimball-based dimensional modeling stages used in this study

2.1. Requirement and Accreditation Indicator Analysis

The input of this step is a set of recurring institutional reporting questions related to digital course delivery, assessment evidence, student participation, lecturer activity, and flexible academic service monitoring. These questions are derived from common accreditation evidence needs in higher education, including traceability of teaching activities, availability of learning materials, assessment records, and student engagement records. The process classifies each requirement into a measurable reporting indicator and determines the required aggregation perspectives, such as semester, academic year, study program, lecturer, course, student, assessment type, and activity type. The output is a requirement matrix that links each reporting indicator to candidate measures and analysis dimensions.

2.2. Data Source Characterization

The model assumes a learning management system that stores course metadata, course topics, learning activities, learning materials, assessment objects, grades, user profiles, enrollment records, and event logs. The study does not depend on a proprietary LMS schema; instead, it uses anonymized or synthetic structures that represent common LMS entities. The input is therefore a generic LMS source characterization rather than raw personal data. The process identifies source entities and maps them to warehouse candidates. The output is a source-to-warehouse mapping in which course, user, activity, material, assessment, grade, and log entities are transformed into facts, dimensions, or bridge-like reporting attributes.

2.3. Data Staging and ETL Preparation

Before the dimensional schema is loaded, LMS operational records are placed in a staging area. The staging layer is needed because LMS log tables are commonly large, event-oriented, and contain repeated or system-generated records. The extract step copies course metadata, user profiles, enrollment records, learning material records, assessment objects, grade records, and event logs into raw staging tables without changing the original operational database. This step preserves source identifiers and source timestamps so that rejected or transformed records can be traced back during audit.

The transformation step standardizes timestamp format, academic period, source user identifier, source course identifier, assessment type, and activity type. Duplicate event records are removed by comparing source user, course, activity type, and event timestamp. System-generated events, background jobs, and non-learning noise events are filtered before loading the activity log fact table. The cleaned source identifiers are then mapped to surrogate keys in shared dimensions, including *dim_date, dim_student, dim_lecturer, dim_course, dim_study_program, dim_assessment_type, and dim_activity*. The load step inserts records into fact_activity_log, fact_teaching_process, and fact_appraisal_process according to the declared grains. Records that cannot be matched to required dimensions are placed in an exception table for data quality review rather than being silently discarded. The staging and ETL preparation process is summarized in Table 2.

Table 2. Staging and ETL preparation for LMS-derived warehouse loading.

ETL Stage	Main Operation	Output	Data Quality Check
Extract	Copy LMS course, user, enrolment, material, assessment, grade, and log records into raw staging tables.	Raw staging tables with source identifiers.	Row counts are compared with source extracts.
Clean and standardize	Normalize timestamp, academic period, user ID, course ID, assessment type, and activity type.	Standardized staging tables.	Invalid timestamps, missing course IDs, and missing user IDs are flagged.
Deduplicate and filter	Remove duplicate log events and exclude system-generated or noise events.	Clean activity-event staging table.	Duplicate removal rate and noise filtering rate are recorded.
Key mapping	Map LMS source IDs to warehouse surrogate keys.	Dimension-key lookup results.	Unmatched keys are written to an exception table.
Fact loading	Load teaching, appraisal, and activity facts based on declared grains.	Populated fact tables.	Fact loading success rate is computed.

2.4. Business Process Selection Criteria

The business processes were selected using three criteria: they had to be directly observable in the LMS data source, they had to relate to at least one monitoring or accreditation reporting indicator, and they had to represent a distinct measurement context to avoid mixing incompatible facts. Based on these criteria, three processes are selected. The teaching delivery process captures course delivery evidence, including topics, activities, and learning materials. The assessment record process captures assignments, examinations, assessment categories, and grades. The activity log process captures recorded user interactions, such as access, login, participation, and other event-based traces. Processes that are not consistently observable or not directly connected to the reporting scope, such as informal communication outside the LMS, are excluded from the current model.

2.5. Formal Fact Grain Definition

The grain is defined before selecting measures to prevent double counting and ambiguous aggregation. The teaching fact grain is one course-delivery evidence item for a specific course, topic, activity or material, lecturer, and date. The assessment fact grain is one assessment result or assessment record for a specific student, course, assessment type, lecturer, and date. The activity log fact grain is one recorded LMS event performed by one user in one course context at one timestamp or date. These grain definitions separate delivery evidence, assessment evidence, and interaction evidence into different fact tables because they represent different event semantics and aggregation rules.

2.6. Dimension and Measure Derivation

Dimensions are derived from attributes required for filtering, grouping, and accreditation evidence tracing. A dimension is included if it is reused by at least one fact table and relates to a reporting perspective, such as time, organizational unit, course, lecturer, student, assessment type, or activity type. Measures are derived from countable events or recorded assessment values. Additive measures include counts of course delivery records, learning materials, assessment records, logins, and recorded activities. Grade-related measures are treated as reportable values that require careful aggregation, such as averages or distributions, rather than unrestricted summation. The output of this step is a set of conformed dimensions and fact measures aligned with the grain definitions.

2.7. Slowly Changing Dimension Policy

Several dimensions in the proposed schema may change over time. Student status, cohort association, study program, lecturer academic unit, and course structure may affect accreditation reporting if only the latest dimension value is retained. Therefore, the model distinguishes between historical changes that must be preserved and simple corrections that can overwrite existing values. Type 2 slowly changing dimensions are used when historical membership, organizational assignment, or course structure must remain traceable across semesters. Type 1 is used for reference labels and typographical corrections that do not represent a meaningful historical change. The SCD policy applied to each dimension in the proposed schema is summarized in Table 3.

Table 3. Slowly changing dimension policy for the proposed schema.

Dimension	SCD Type	Rationale
dim_student	Type 2	Preserves historical changes in study program, status, and cohort for semester-based accreditation reporting.
dim_lecturer	Type 2	Preserves historical academic unit, role, or lecturer assignment changes.
dim_course	Type 2 for structural changes; Type 1 for corrections	Major changes in course code, curriculum placement, or credit structure are historized, while spelling corrections overwrite the previous value.
dim_faculty and dim_study_program	Type 2	Preserves organizational restructuring and program identity changes across reporting periods.
dim_activity and dim_assessment_type	Type 1	Reference labels are generally corrected rather than historized.
dim_date	Fixed dimension	Calendar and academic-period attributes are maintained as a stable reference dimension.

2.8. Schema Construction

The schema is constructed using the Kimball approach because it is compatible with incremental development of process-specific data marts and shared conformed dimensions [5, 6]. The process starts by constructing a bus matrix, then translating the selected processes into star schemas. Shared dimensions, such as date, faculty, study program, student, lecturer, and course, are reused across fact tables when their semantics are consistent. The output is a reporting-oriented dimensional model consisting of three fact tables and eleven dimension tables.

2.9. Implementation Procedure

The implementation procedure translates the conceptual schema into physical tables using surrogate keys, foreign keys, and representative measures. Because institutional student data are sensitive, this study assumes anonymized or synthetic LMS records for implementation examples. The procedure consists of creating dimensions, loading conformed dimension keys, loading fact records according to the declared grain, and checking sample reporting queries. The implementation is minimal and schema-oriented; it is not intended to claim production-level scalability.

2.10. Proof-of-Concept Evaluation Metrics

To strengthen the assessment beyond schema representation, this study defines a limited proof-of-concept evaluation using anonymized or synthetic LMS-like records. The evaluation is not intended to represent production performance. It is used to check whether the staging and dimensional schema can be loaded and queried with measurable operational indicators. The metrics include ETL processing time, duplicate or noise removal rate, fact loading success rate, query latency for selected reporting scenarios, join complexity reduction compared with direct operational-style reporting, and indicator coverage ratio. These proof-of-concept evaluation metrics are summarized in Table 4.

Table 4. Proof-of-concept evaluation metrics.

Metric	Measurement Method	Purpose
ETL processing time	Measure elapsed time from staging insertion to fact loading.	Indicates feasibility of the proposed ETL sequence on sample records.
Duplicate or noise removal rate	Divide removed duplicate and system-generated events by total staged log events.	Checks whether messy LMS logs are cleaned before loading fact_activity_log.
Fact loading success rate	Divide valid loaded fact records by cleaned staging records.	Checks surrogate-key mapping and load completeness.
Query latency	Measure elapsed time of representative star-schema reporting queries.	Provides limited evidence of report query feasibility.
Join complexity reduction	Compare the number of joins in operational-style reporting queries and star-schema reporting queries.	Examines whether the schema simplifies report formulation.
Indicator coverage ratio	Divide covered reporting indicators by the indicators listed in the reporting mapping table.	Measures requirement representation in the schema.

2.11. Validation and Evaluation Protocol

The artifact is assessed using five checks. First, requirement coverage checks whether each selected monitoring or accreditation indicator has at least one fact table, measure, and dimension path. Second, scenario-based validation executes representative reporting queries against the physical schema blueprint to check whether the schema expresses the intended report structure. Third, limited ETL and query evaluation measures the proof-of-concept metrics in Table 4 using synthetic LMS-like records. Fourth, dashboard prototype mapping links the fact tables to dashboard components for active course monitoring, material availability, assessment monitoring, student participation, and accreditation summary reporting. Fifth, operational reporting comparison analyzes whether the dimensional schema reduces direct dependence on normalized LMS operational tables by consolidating reporting logic into fact and dimension tables. These evaluations remain limited to artifact feasibility and reporting coverage; they do not claim production-scale ETL throughput, completed SUS-based dashboard usability testing, or predictive model accuracy.

3. Results

3.1. Business Process Matrix

After the facts and dimensions are identified, a bus matrix is constructed to map the relationship between business processes and dimensions. The bus matrix acts as a blueprint for the data warehouse design. Figure 2 shows the relationship between the three selected fact tables and their corresponding dimensions.

	date	faculty	studyprogram	student	lecturer	course	course topic	course_activities	course material	assesment type	activity
teaching process	v	v	v	v	v	v	v	v	v		
appraisal process	v	v	v	v	v	v	v		v	v	
activity log	v	v	v	v		v	v	v			

Figure 2. Business process matrix for e-learning monitoring.

Based on the bus matrix, the teaching process is related to date, faculty, study program, student, lecturer, course, course topic, course activity, and course material dimensions. The appraisal process is related to date, faculty, study program, student, lecturer, course, course topic, course material, and assessment type dimensions. The activity log is related to date, faculty, study program, student, course, course topic, course activity, and activity dimensions.

3.2. Fact Table and Dimension Identification

The proposed fact tables are summarized in Table 5. Each fact table corresponds to one business process and stores measures intended for monitoring and reporting.

Table 5. Proposed fact tables.

Fact Table	Description
fact_teaching_process	Stores teaching process indicators, such as course delivery, learning activities, and learning material records.
fact_appraisal_process	Stores appraisal indicators, such as assignments, examinations, assessment types, and student grades.
fact_activity_log	Stores activity log indicators, such as login records and student interactions in the e-learning system.

Table 6. Proposed dimension tables.

Dimension Table	Description
dim_date	Stores date, week, month, semester, academic year, and update time.
dim_faculty	Stores faculty information.
dim_study_program	Stores study program information.
dim_student	Stores student profile information.
dim_lecturer	Stores lecturer profile information.
dim_course	Stores course information.
dim_course_topic	Stores learning topic information.
dim_course_activities	Stores learning activity information.
dim_course_material	Stores learning material information.
dim_assessment_type	Stores assessment type information.
dim_activity	Stores e-learning activity type information.

The fact table design in Table 5 separates the measurement context of teaching, appraisal, and activity log processes. This separation is intended to keep the indicators traceable and to provide different aggregation paths for monitoring and reporting. The proposed dimension tables are summarized in Table 6. These dimensions define contextual attributes for analyzing e-learning activities from different perspectives.

3.3. Formal Grain and Measure Specification

The formal grain and representative measures are summarized in Table 7. The table is used to make the reporting semantics explicit before physical schema construction. This step is important because the same LMS entity can produce different analytical events. For example, a course material upload is not equivalent to a student activity event, and a grade record is not equivalent to a course delivery record.

Table 7. Formal fact grain and representative measures.

Fact Table	Declared Grain	Representative Measures	Aggregation Notes
fact_teaching_process	One course-delivery evidence item for one course, topic, activity or material, lecturer, and date.	Course delivery count, activity count, material count.	Additive across date, course, lecturer, study program, and faculty.
fact_appraisal_process	One assessment record or grade record for one student, course, assessment type, lecturer, and date.	Assessment count, submission count, grade value.	Counts are additive; grade values require average, distribution, or threshold-based reporting.
fact_activity_log	One recorded LMS event performed by one user in one course context at one timestamp or date.	Login count, activity count, participation event count.	Additive across time, activity type, course, student, and study program; event duplication must be removed during ETL.

Table 7 clarifies that the model separates delivery evidence, assessment evidence, and interaction evidence. This separation avoids joining heterogeneous events into a single fact table and is intended to reduce the risk of double counting when preparing accreditation summaries.

3.4. Mapping of Reporting Needs to the Proposed Schema

To illustrate the practical relevance of the proposed model, several reporting needs are mapped to the corresponding fact and dimension tables, as shown in Table 8. This mapping indicates how selected institutional reporting questions can be represented using the proposed dimensional schema.

The mapping indicates that the proposed schema is intended to support selected institutional reports without directly querying the operational e-learning database. For example, reports on course activity can be expressed through *fact_teaching_process*, whereas reports on student participation can be expressed through *fact_activity_log*. This separation may improve reporting consistency because each business process has a clearly defined fact table and grain.

Table 8. Mapping of reporting needs to fact and dimension tables.

Reporting Need	Main Indicator	Fact Table	Relevant Dimensions
Monitoring active courses per semester	Number of active courses and course delivery records	fact_teaching_process	Date, study program, lecturer, course
Monitoring uploaded learning materials	Number of uploaded materials by course and semester	fact_teaching_process	Date, course, course topic, course material, lecturer
Monitoring assessment activities	Number of assignments, examinations, and assessment records	fact_appraisal_process	Date, course, lecturer, student, assessment type
Monitoring student grades	Student grade distribution across courses and semesters	fact_appraisal_process	Date, student, course, study program, assessment type
Monitoring student participation	Login frequency and number of e-learning interactions	fact_activity_log	Date, student, course, activity
Monitoring digital academic services under flexible learning conditions	Summary of online course delivery, assessment, and student participation	All fact tables	Date, faculty, study program, course, lecturer, student
Accreditation-related reporting	Summary of teaching, assessment, and student activity indicators	All fact tables	Date, faculty, study program, course, lecturer, student

Table 9. Mapping of structured LMS-derived accreditation evidence to schema components.

Accreditation Evidence Need	Structured LMS Indicator	Schema Component	Scope Boundary
Evidence of course delivery	Active course records, topics, activities, and uploaded materials.	fact_teaching_process, dim_course, dim_course_topic, dim_course_material.	Represents digital course delivery traces, not syllabus quality or classroom observations.
Evidence of assessment implementation	Assessment objects, submission records, assessment type, and grade values.	fact_appraisal_process , dim_assessment_type, dim_student, dim_course.	Represents structured assessment records, not rubric validity or qualitative feedback quality.
Evidence of student engagement	Login counts, activity counts, and participation events.	fact_activity_log, dim_activity, dim_student, dim_date.	Represents LMS-recorded events, not offline participation or unrecorded interaction.
Evidence of program-level digital academic service	Aggregated teaching, assessment, and activity indicators by study program and period.	All fact tables with dim_study_program, dim_faculty, and dim_date.	Represents structured digital service indicators, not full institutional accreditation narratives.

3.5. Accreditation Evidence Scope

The accreditation scope of this study is limited to structured evidence that can be derived from LMS records. It does not cover qualitative accreditation narratives, policy documents, curriculum documents, meeting minutes, or external quality assurance files. Table 9 maps generic structured evidence needs to the schema components used in this study.

3.6. Data Warehouse Schema for Accreditation Reporting

Based on the proposed fact and dimension tables, several analytical reports can be specified for e-learning monitoring and accreditation reporting. These reports are derived from the relationship between fact tables as measurable events and dimension tables as analytical perspectives. Table 10 presents examples of analytical reports that can be represented by the proposed schema.

The analytical reports in Table 10 illustrate that the proposed schema can represent selected operational monitoring and institutional reporting scenarios. For example, active course monitoring and learning material availability can be expressed through the teaching process schema, whereas assessment activity and student grade reports can be expressed through the appraisal process schema. Student participation reports can be expressed through the activity log schema. These reports can also be aggregated at the faculty, study program, semester, and academic year levels for accreditation-related documentation.

The report examples also define the content basis for a dashboard prototype. Each report has a corresponding measure, analysis perspective, and supporting schema, which indicates that the proposed model can be connected to business intelligence tools such as Power BI Desktop, Grafana, or Looker Studio.

Table 10. Analytical reports supported by the proposed schema.

Analytical Report	Main Measure	Analysis Perspective	Supporting Schema
Active course monitoring	Number of active courses and course delivery records	Semester, academic year, study program, lecturer, course	fact_teaching_process, dim_date, dim_study_program, dim_lecturer, dim_course
Learning material availability	Number of uploaded learning materials for each course	Semester, course topic, lecturer, study program	fact_teaching_process, dim_course, dim_course_topic, dim_course_material, dim_lecturer
Assessment activity monitoring	Number of assignments, examinations, and assessment records	Semester, course, lecturer, assessment type	fact_appraisal_process, dim_date, dim_course, dim_lecturer, dim_assessment_type
Student grade monitoring	Student grade distribution and assessment results	Semester, student, course, study program, assessment type	fact_appraisal_process, dim_student, dim_course, dim_study_program, dim_assessment_type

Analytical Report	Main Measure	Analysis Perspective	Supporting Schema
Student participation monitoring	Number of logins and recorded e-learning activities	Week, month, semester, student, course, activity type	fact_activity_log, dim_date, dim_student, dim_course, dim_activity
Lecturer teaching activity monitoring	Number of delivered courses, uploaded materials, and learning activities	Lecturer, course, study program, semester	fact_teaching_process, dim_lecturer, dim_course, dim_study_program, dim_date
Digital academic service monitoring under flexible learning conditions	Summary of online teaching, assessment, and student activity indicators	Academic year, semester, study program, lecturer, student	fact_teaching_process, fact_appraisal_process, fact_activity_log, and shared dimensions
Accreditation reporting summary	Aggregated evidence of teaching activities, assessment records, and student participation	Faculty, study program, academic year, semester, course	All fact tables and related dimensions

3.7. Reference Schema Blueprint

The conceptual model was translated into an implementable reference schema blueprint. The reference schema is not presented as a deployed production system; it is a reproducible physical design that specifies keys, main attributes, measures, foreign-key relationships, and fact grain. The implementation assumes anonymized or synthetic LMS records and uses surrogate keys for dimensions. Table 11 summarizes the main physical schema elements.

For reproducibility purposes, the complete reference SQL schema is provided in Appendix A. The schema is illustrative and not intended as a production implementation.

The reference schema is designed to express monitoring and accreditation queries while reducing the need to specify repeated joins over normalized operational LMS tables. For example, active course monitoring by semester and study program can be expressed through the teaching fact table and shared dimensions, as shown in Figure 3.

```
SELECT d.academic_year,
    d.semester,
    sp.study_program_name,
    COUNT(DISTINCT f.course_key) AS active_courses,
    SUM(f.material_count) AS uploaded_materials
FROM fact_teaching_process f
JOIN dim_date d ON f.date_key = d.date_key
JOIN dim_study_program sp ON f.study_program_key = sp.study_program_key
GROUP BY d.academic_year, d.semester, sp.study_program_name;
```

Figure 3. Illustrative accreditation-oriented monitoring query.

The query example illustrates how course delivery evidence and learning material availability can be aggregated by reporting period and study program. Similar queries can be constructed for assessment records and activity logs using the fact tables listed in Table 10.

Table 11. Reference schema blueprint for reproducible implementation.

Table	Primary Key	Main Attributes / Foreign Keys	Measures	Grain
dim_date	date_key	full date, week, month, semester, academic year.	Not applicable.	One calendar or academic date.
dim_course	course_key	course code, course name, credit, course category.	Not applicable.	One course identity.
dim_student	student_key	anonymous student ID, cohort, study program key.	Not applicable.	One student identity.
dim_lecturer	lecturer_key	anonymous lecturer ID, academic unit.	Not applicable.	One lecturer identity.
fact_teaching_process	teaching_fact_key	date, course, topic, activity, material, lecturer, study program keys.	delivery count, material count.	One course-delivery evidence item.
fact_appraisal_process	appraisal_fact_key	date, course, student, lecturer, assessment type keys.	assessment count, submission count, grade value.	One assessment or grade record.
fact_activity_log	activity_log_fact_key	date, course, student, activity, study program keys.	event count, login count.	One LMS event or declared aggregate event record.

3.8. Dimensional Model

The first schema is the teaching process schema. It connects fact_teaching_process with dimensions related to teaching activities, including date, faculty, study program, student, lecturer, course, course topic, course activities, and course material. This schema is intended to support reports such as the number of active courses, distribution of learning materials, and course delivery monitoring across study programs. As shown in Figure 4, the teaching process schema places the measurable teaching event at the center of shared descriptive dimensions.

The second schema is the appraisal process schema. It connects fact_appraisal_process with dimensions related to assessment records. This schema can be used to represent assessment completeness, student grades, and course-based evaluation activities. Figure 5 presents the appraisal process star schema and shows how assessment records are related to student, lecturer, course, date, and assessment type dimensions.

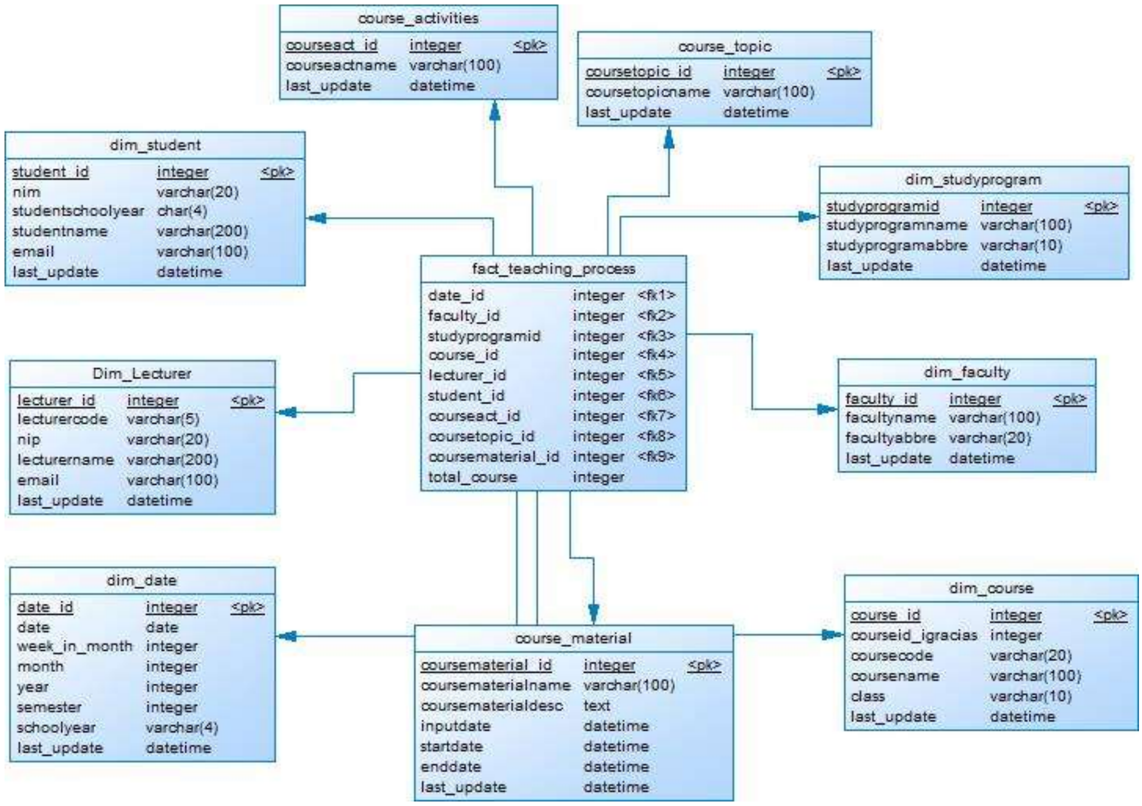

Figure 4. Teaching process star schema.

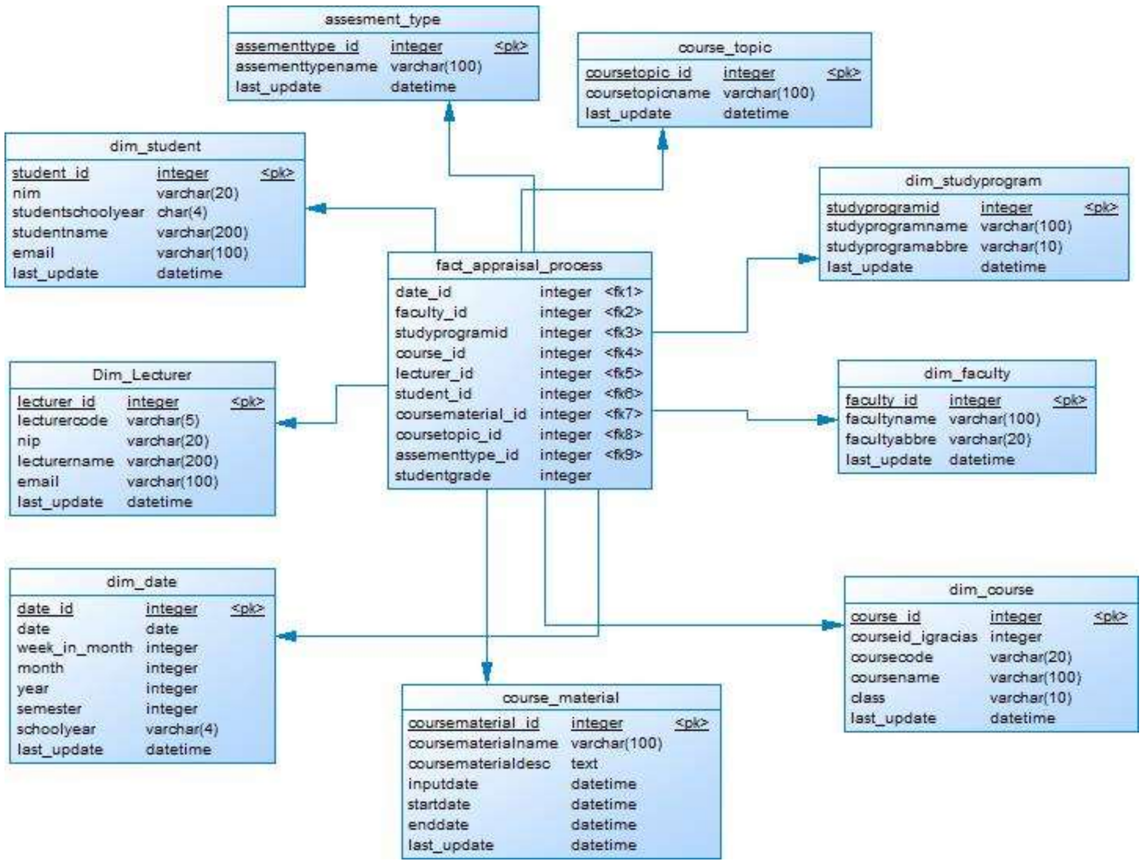

Figure 5. Appraisal process star schema.

3.9. Reporting and Monitoring Outputs

The third schema is the activity log schema. It connects fact_activity_log with dimensions that describe student interactions in the e-learning platform. This schema is intended to support reports such as student login frequency, activity distribution, and participation trends. The activity log schema is relevant because it represents evidence of student engagement and may be used as an input for learning analytics.

The example reporting outputs include active course monitoring, learning material availability, assessment activity monitoring, student grade monitoring, student participation monitoring, lecturer teaching activity monitoring, digital academic service monitoring under flexible learning conditions, and accreditation reporting summaries. These outputs are represented by the mapping in Table 8 and the report examples in Table 10.

3.10. Dashboard Prototype and Review Criteria

To connect the schema artifact with accreditation reporting practice, the proposed warehouse was mapped into a one-page dashboard prototype. The prototype is intended for quality assurance stakeholders who need a compact view of structured LMS evidence. The dashboard design contains five panels: active course monitoring, learning material availability, assessment activity monitoring, student participation monitoring, and accreditation reporting summary. The prototype does not replace the data warehouse design; rather, it demonstrates that the measures and dimensions in the proposed schema can be translated into dashboard components. The dashboard prototype components and their review criteria are summarized in Table 12.

Table 12. Dashboard prototype components derived from the proposed schema.

Dashboard Panel	Displayed Indicator	Main Schema Source	Review Criterion
Active course monitoring	Active courses and delivery records by semester and study program	fact_teaching_process, dim_date, dim_course, dim_study_program	Stakeholders can identify course delivery coverage by period.
Learning material availability	Uploaded material count by course, lecturer, and topic	fact_teaching_process, dim_course_material, dim_lecturer	Stakeholders can locate courses with missing or limited digital materials.
Assessment activity monitoring	Assessment count, submission count, and grade availability	fact_appraisal_process, dim_assessment_type, dim_course	Stakeholders can check whether assessment evidence exists for selected courses.
Student participation monitoring	Login count and activity event count by course and student group	fact_activity_log, dim_activity, dim_student	Stakeholders can observe participation trends and low-activity courses.
Accreditation reporting summary	Aggregated teaching, assessment, and participation indicators by study program	All fact tables and shared dimensions	Stakeholders can export structured evidence for accreditation preparation.

Because this study uses synthetic LMS-like records and does not involve deployment in an institutional quality assurance unit, the dashboard component is reported as a prototype mapping and review protocol rather than as a completed usability evaluation. The prototype demonstrates how each analytical report in the proposed schema can be translated into dashboard panels, indicators, dimension filters, and review criteria. A formal SUS-based evaluation with three to five BPM or UPM staff is recommended as the next validation stage after the schema is populated with real institutional data and implemented in a dashboard environment such as Power BI Desktop, Grafana, or Looker Studio.

3.11. Limited ETL and Query Evaluation

A limited proof-of-concept was conducted using synthetic LMS-like activity records in a local SQLite environment. The synthetic dataset contained course identifiers, user identifiers, activity types, event timestamps, and system-event flags. The evaluation loaded records into staging tables, removed duplicate and system-generated events, mapped source identifiers to surrogate keys, loaded fact_activity_log, and executed representative reporting queries. The proof-of-concept was executed on a local SQLite database with single-user execution and without concurrent dashboard access. Therefore, the reported latency values should be interpreted only as local feasibility indicators. The observed ETL and query evaluation results are summarized in Table 13.

Table 13. Limited proof-of-concept ETL and query evaluation using synthetic LMS-like records.

Metric	Observed Value	Interpretation
Staged log records	52,500 records	Synthetic activity-log records were inserted into the staging table.
System-generated events	7,437 records	These records were filtered before loading the activity fact table.
Cleaned activity records	42,908 records	Records remaining after duplicate and noise filtering.
Duplicate or noise removal rate	18.27%	Indicates the importance of cleaning LMS logs before analytical loading.
Fact loading success rate	100.00%	All cleaned records were matched to surrogate keys and loaded into fact_activity_log.
ETL processing time	0.117 seconds	Local proof-of-concept elapsed time from staging insertion to fact loading.
Average star-schema query latency	27.03 ms	Average of 30 runs for a representative activity reporting query.
Average operational-style query latency	28.02 ms	Average of 30 runs over cleaned operational-style records; reported only as a local comparison.
Join complexity	2 joins versus 4 logical joins	The star schema expresses the reporting query with fewer explicit joins than the operational-style formulation.

The proof-of-concept supports two limited observations. First, the ETL preparation step is necessary because duplicate and system-generated events account for a non-trivial portion of staged log records. Second, the star schema simplifies report formulation by moving repeated key mapping and cleaning logic into the warehouse layer. The latency values should not be generalized to production LMS workloads because they depend on local hardware, database engine, indexing strategy, and data volume.

3.12. Schema Validation

The proposed model was assessed through schema validation, proof-of-concept metrics, and dashboard prototype mapping. The validation uses the reporting needs in Table 8 as the indicator set. A requirement is considered represented when the schema provides a fact table, at least one measure, and the required dimensions for filtering or aggregation. Table 14 defines the validation objectives, methods, criteria, assumptions, and limitations.

Table 14. Schema validation matrix.

Validation Objective	Method	Criteria	Assumptions	Limitations
Requirement coverage	Map each reporting need to fact tables, measures, and dimensions.	A need is represented if a schema path exists for the required measure and aggregation perspective.	Reporting needs are limited to structured LMS-derived indicators.	Does not validate non-LMS evidence or qualitative accreditation artifacts.
Grain consistency	Check whether each report uses a fact table whose declared grain matches the reporting event.	No report combines heterogeneous event semantics in a single fact table.	Teaching, assessment, and activity events are separable during ETL.	Does not test ETL error rates or source-system data quality.
Reference schema implementability	Translate the dimensional model into keys, attributes, measures, and pseudo-DDL.	Each fact table has a primary key, foreign-key paths, measures, and a declared grain.	Institutions can map their LMS entities to the generic source characterization.	Does not claim production deployment or runtime scalability.
Reporting scenario validity	Formulate representative query scenarios over the reference schema.	Each scenario can be expressed using fact and dimension tables without direct operational joins.	Queries operate on anonymized or synthetic LMS-derived records.	Does not benchmark production query latency or concurrent dashboard use.
ETL and query feasibility	Load synthetic LMS-like records through staging, cleaning, key mapping, and fact loading.	ETL metrics and representative query latency can be measured.	Synthetic records approximate common LMS activity-log fields.	Does not represent production workload, indexing, concurrency, or infrastructure.
Dashboard prototype mapping	Map schema measures to a one-page accreditation monitoring dashboard.	Each dashboard component has a fact table, measure, dimension filter, and review criterion.	Dashboard panels use structured LMS-derived indicators.	Does not replace full SUS testing with real institutional users.

Based on this validation matrix, the main reporting scenarios were then checked against the available fact and dimension paths. The scenario-based validation results are presented in Table 15.

Table 15. Scenario-based schema validation of monitoring and accreditation reporting needs.

Validation Scenario	Required Evidence	Coverage Result	Schema Path
Active course evidence by semester	Course delivery records by period and study program	Covered	fact_teaching_process, dim_date, dim_course, dim_study_program
Learning material availability	Uploaded material count by course and lecturer	Covered	fact_teaching_process, dim_course_material, dim_lecturer, dim_course
Assessment evidence	Assignment, examination, and grade records	Covered	fact_appraisal_process, dim_assessment_type, dim_student, dim_course
Student participation evidence	Login and activity events by student and course	Covered	fact_activity_log, dim_activity, dim_student, dim_course
Integrated accreditation summary	Teaching, assessment, and participation evidence across study programs	Partially represented	All fact tables and shared dimensions; narrative evidence and document attachments require additional metadata tables.

The evaluation indicates that the schema includes paths for the main structured indicators used in this study. The integrated accreditation summary is only partially represented because accreditation evidence may include narrative documents, policy files, and qualitative evaluations that are not stored as LMS events. This limitation prevents the paper from claiming complete accreditation system coverage.

Compared with direct operational reporting, the dimensional schema consolidates reporting logic into stable fact and dimension tables. A normalized LMS database may require repeated joins across course, user, grade, material, and log tables for each report. In contrast, the proposed schema organizes these entities according to reporting grains. This comparison is qualitative and schema-based; no production query runtime, efficiency, or scalability claim is made.

4. Discussion

Compared with recent learning analytics and dashboard-oriented studies, the proposed model focuses on the analytical data structure required before visualization or prediction can be performed. The contribution is not a new dimensional modeling algorithm, but a domain-specific schema artifact for accreditation-oriented e-learning reporting. This positioning is important because accreditation reporting requires traceable evidence, stable aggregation semantics, and separation between different types of academic records. By defining distinct grains for teaching delivery, assessment records, and activity logs, the model is intended to reduce ambiguity that may occur when heterogeneous LMS events are aggregated without a declared measurement context.

The main difference between the proposed model and a generic e-learning data warehouse lies in its requirement-to-schema orientation. A generic LMS warehouse may store course, user, grade, and activity data for broad analytics. In contrast, this model starts from monitoring and accreditation reporting scenarios, defines the evidence needed for each scenario, and then maps each scenario to fact grains and conformed dimensions. This positioning makes the model easier to evaluate as an institutional reporting artifact, although it remains less general than an enterprise-wide academic data warehouse.

The proposed data warehouse model may reduce some reporting complexity by separating analytical data from operational data. Instead of writing report-specific queries directly on normalized LMS tables, institutional stakeholders can use structured fact and dimension tables aligned with reporting grains. This design also provides structures for historical reporting because the date dimension enables analysis across semester, month, week, or academic year. However, this paper does not claim measured runtime improvement because production workloads and operational database benchmarks were not evaluated.

A potential advantage is the clearer specification of reporting indicators. By defining fact table grains explicitly, the institution may reduce ambiguity in interpreting e-learning measures. For example, teaching activities, appraisal activities, and activity logs are stored in different fact tables because they represent different business processes and measurement contexts. This separation may make the data model easier to maintain and extend.

The proposed model is intended to be relevant to flexible academic service conditions. When flexible work arrangements or proportional distance learning are implemented, institutions need reliable indicators to examine whether course delivery, assessment processes, and student participation remain traceable. The proposed data warehouse model defines an analytical structure for transforming e-learning records into monitoring indicators that may support institutional evaluation and accreditation reporting.

The proposed model may be used as a basis for dashboard development. Each fact table can be connected to visualization components such as course activity dashboards, assessment monitoring dashboards, student participation dashboards, and digital academic service monitoring dashboards. In the limited prototype mapping, each panel was linked to a fact table, measure, dimension filter, and review criterion. This mapping indicates that the schema can support dashboard construction, although a complete dashboard usability test with institutional stakeholders is still required before deployment.

4.1. Integration with Accreditation Document Management Systems

The current schema intentionally focuses on structured LMS evidence. However, accreditation work also requires qualitative and documentary evidence, including curriculum documents, policy documents, meeting minutes, internal quality assurance reports, external audit files, and narrative descriptions. These artifacts should not be forced into the LMS activity fact tables because their grain and evidence semantics differ from teaching, assessment, and activity-log events.

A practical extension is to integrate the warehouse with an accreditation document management system (DMS). In this extension, structured LMS indicators remain in the three fact tables, while document evidence is represented through additional metadata dimensions and a separate evidence fact table. The recommended extension includes dim_document_type, dim_accreditation_standard, dim_evidence_source, and fact_accreditation_evidence. The evidence fact table can store or reference metadata such as document_url, storage_location, evidence_status, uploaded_by, verified_by, and verification_date. This design keeps structured LMS indicators analytically clean while allowing accreditation dashboards to link quantitative evidence with supporting documents. The recommended metadata dimensions and evidence fact table for this extension are summarized in Table 16.

With this extension, an accreditation dashboard could present quantitative indicators from LMS facts and provide drill-through links to supporting documents stored in a DMS or cloud repository. The integration should use access controls and anonymization rules because accreditation documents may include personal, academic, or institutional quality assurance information.

Table 16. Recommended extension for accreditation document management integration.

Proposed Table	Representative Attributes	Purpose
dim_document_type	document type, document category, retention period	Classifies curriculum files, policy files, minutes, audit reports, and narrative evidence.
dim_accreditation_standard	standard code, criterion, element, indicator group	Connects evidence to accreditation standards and assessment elements.
dim_evidence_source	source system, owner unit, upload channel	Describes whether evidence comes from LMS, DMS, academic system, or quality assurance unit.
fact_accreditation_evidence	date key, study program key, standard key, document type key, evidence status, document URL, uploaded by, verified by, verification date	Stores evidence-submission and verification events without mixing document metadata into LMS activity facts.

4.2. Limitations

This study has several limitations. First, the implementation is presented as a physical schema blueprint and a limited proof-of-concept using synthetic LMS-like records, not as a production data warehouse populated with real institutional data. Second, the ETL and query measurements are local feasibility indicators and should not be interpreted as production throughput, scalability, indexing, or concurrency results. Third, the dashboard contribution is limited to prototype mapping and review criteria; a complete SUS-based usability test with BPM or UPM stakeholders remains future work. Fourth, accreditation reporting is represented through structured LMS evidence, whereas full accreditation processes require qualitative documents, policy evidence, curriculum artifacts, and external quality assurance records. Fifth, the model is based on common LMS entities and may require adaptation for institutions with different LMS structures, competency-based curricula, or multi-platform learning ecosystems.

5. Conclusions

This study examined the problem of manual and fragmented e-learning monitoring for accreditation-related reporting in higher education. The paper contributes a domain-specific Kimball-based modeling procedure that links reporting requirements to business processes, formal fact grains, measures, conformed dimensions, physical schema elements, and validation scenarios. The main result is a reporting-oriented model consisting of three fact tables, namely fact_teaching_process, fact_appraisal_process, and fact_activity_log, supported by eleven dimension tables.

The revised model defines a structured schema for integrating e-learning evidence, monitoring active courses, tracking learning material availability, analyzing assessment activities, observing student participation, and preparing structured accreditation reporting summaries. It also specifies staging and ETL preparation, slowly changing dimension policies, proof-of-concept evaluation metrics, dashboard prototype components, and a DMS-oriented extension for qualitative accreditation evidence. The scenario-based validation indicates that the schema includes paths for the selected structured indicators, while integrated accreditation evidence remains only partially represented unless the warehouse is connected to document management metadata. Future work should populate the schema with real institutional data, implement full extract-transform-load processes, evaluate query performance and dashboard usability with quality assurance stakeholders, and investigate whether the warehouse can be extended for learning analytics and academic decision support.

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