IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Submitted for academic assessment, 2025

Digital Object Identifier

A PRISMA-Guided Systematic Literature Review on Cost-Effective ETL Pipelines and Data Warehousing for Higher Education Institutions in Uganda. A case Study of Uganda Christian University

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ABSTRACT Higher Education Institutions (HEIs) increasingly rely on data-driven infrastructures to strengthen governance, improve operational efficiency, and support evidence-based student success initiatives. In developing contexts such as Uganda and specifically at Uganda Christian University (UCU), institutional modernization is hindered by fragmented data sources, manual reporting workflows, and limited analytics capacity. Prior studies underscore the growing role of big data and business intelligence in transforming higher education management [1], [2].
Guided by the PRISMA 2020 framework [3], this systematic review synthesizes 24 Web of Science and SCOPUS indexed studies (2000–2025) examining Extract Transform Load (ETL) processes, data warehousing (DW) architectures and analytics adoption in HEIs. The review identifies recurring themes, including multidimensional DW modelling, ETL process optimization, knowledge management integration and the shift toward hybrid cloud infrastructures. Existing research shows that well designed BI and DW systems can significantly improve planning, reporting and institutional decision making.
The findings further indicate that educational data mining and learning analytics enabled by machine learning techniques and structured analytical workflows play a vital role in student performance prediction, retention analysis and academic risk detection [4]. However, HEIs in low resource environments continue to face challenges such as inadequate infrastructure, limited data governance maturity, and high implementation costs, which mirror the constraints observed at UCU.
In response, this review proposes a cost effective hybrid local cloud DW architecture tailored to the operational realities of Uganda Christian University. The proposed framework incorporates automated ETL pipelines, data quality controls and scalable analytics modules capable of supporting both institutional reporting and advanced learning analytics. The study concludes by outlining an implementation road map and identifying future research directions for sustainable, analytics ready infrastructures in Ugandan HEIs.

INDEX TERMS ETL, Data Warehouse, Higher Education, PRISMA, Uganda, Predictive Analytics, Business Intelligence

Common Abbreviations Used in This Study

Abbreviation	Meaning
HEI	Higher Education Institution
ETL	Extract–Transform–Load
DW	Data Warehouse
BI	Business Intelligence
LMS	Learning Management System
SIS	Student Information System
ML	Machine Learning
API	Application Programming Interface
DBMS	Database Management System
RDBMS	Relational Database Management System
CDC	Change Data Capture
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
EDM	Educational Data Mining
CRISP-DM	Cross-Industry Standard Process for Data Mining

I. INTRODUCTION

Higher Education Institutions (HEIs) increasingly rely on data-driven approaches to enhance governance, quality assurance and student success. The rapid expansion of institutional data has intensified the need for reliable mechanisms to integrate and analyze information for strategic decision-making. Extract–Transform–Load (ETL) processes and data warehousing (DW) architectures provide the technological foundation for unified, analytics-ready data environments within universities [5], [6]. Prior studies emphasize that well-designed ETL workflows and DW structures enable efficient reporting, longitudinal analysis, and operational visibility across academic and administrative units [1], [2].

Despite these global advancements, many universities in developing regions face persistent technical and organizational limitations. Research shows that institutions in low resource settings commonly struggle with fragmented systems, manual data handling, inconsistent data quality, and limited automation capacity [7], [8]. Uganda Christian University (UCU), like other Ugandan HEIs, operates multiple independent platforms including LMS, SIS, and finance systems which complicates data integration and inhibits the adoption of comprehensive DW or analytics solutions [9]. These challenges restrict the institution's ability to support evidence based decision-making and advanced analytics.

The objective of this project is to synthesize existing empirical and technical evidence on ETL pipelines, DW architectures and analytics adoption in higher education and to use these insights to propose a practical, cost-effective and scalable data architecture tailored to Ugandan HEIs. Building on documented best practices in ETL automation, multidimensional modeling, governance and BI integration [10], [11], the project develops a hybrid local–cloud framework designed to address infrastructural constraints while enabling progressive analytics capability. To achieve this, the study applies the PRISMA 2020 systematic review methodology to analyze 24 SCOPUS-indexed studies (2000–2025), consolidating their findings into a coherent modernization roadmap specifically aligned to the operational realities of UCU and related institutions in Uganda.

II. BACKGROUND OF THE STUDY

A. GLOBAL HEI PRACTICES

Globally, HEIs operate mature data ecosystems characterized by automated ETL workflows, centralized DWs and structured data governance processes. Such environments support predictive analytics, learning analytics and operational dashboards that improve institutional planning and performance. Studies show that universities in technologically advanced regions achieve significant benefits through enterprise BI and hybrid architecture models [11]. Educational data mining and learning analytics are well established in North American and European universities, where DW-supported analytics enhance student monitoring, retention, and instructional improvement [4], [12]. Practical deployments, such as Cornell University's automated DW environment, illustrate the efficiency gains achievable through scalable data infrastructures [13].

B. AFRICAN AND UGANDAN CONTEXT

In many African HEIs, the adoption of DW and ETL technologies remains limited due to fragmented systems, manual data handling procedures and inconsistent reporting practices [8]. Ugandan universities face additional challenges such as intermittent connectivity, limited technical expertise and restricted budgets, which further impede the adoption of modern analytical systems [9]. At UCU, institutional data is distributed across platforms such as LMS, SIS, and administrative systems, resulting in redundancy and limited analytical capability. These constraints highlight the need for affordable, scalable data architectures that align with the operational realities of Ugandan HEIs.

III. METHODOLOGY (PRISMA PROTOCOL)

This review followed the PRISMA 2000/2020 principles. The search strategy targeted SCOPUS and Web of Science with keyword combinations capturing ETL, data warehousing, analytics and higher education. The search was restricted to English-language publications (2015–2025). The review comprised four stages: identification, screening, eligibility and inclusion.

A. SEARCH STRATEGY AND SOURCES

Search strings included:

- `("ETL" OR "Extract Transform Load") AND "Higher Education"`
- `("Data Warehouse" OR "Data Warehousing") AND ("University" OR "Tertiary")`
- `"Predictive Analytics" AND "Education"`

Records were exported to a reference manager for deduplication and screening.

B. INCLUSION CRITERIA

- Peer-reviewed studies (journal or conference) focusing on ETL, DW, BI, or analytics within HEIs.
- Empirical, architectural, or implementation-oriented studies.
- English-language full-texts available.
- Studies published between 2015 and 2025 (to capture contemporary architectures and tools).

C. EXCLUSION CRITERIA

- Studies outside higher education (e.g., retail, general industry) without transferable HEI implications.
- Non-empirical opinion pieces, editorials and blog posts.
- Abstract-only records or inaccessible full texts.
- Papers focusing exclusively on theoretical aspects without implementation or architectural relevance.

IV. STUDY SELECTION

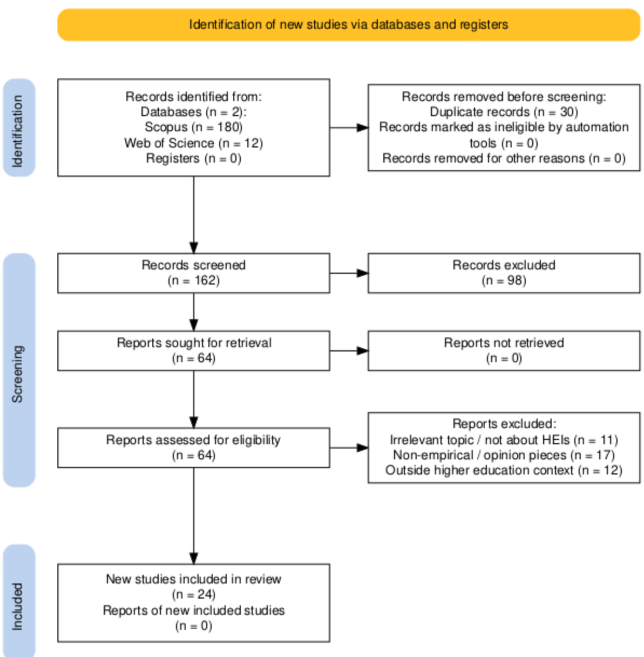

FIGURE 1: PRISMA 2020 flow diagram of the study selection process (24 studies included).

V. INCLUDED STUDIES

TABLE 1: Summary of the 24 included SCOPUS-indexed studies.

Citation	Title / Focus	Year
[14]	Big data for university education management	2021
[1]	Big data, data science and analytics in IS research	2014
[15]	Data warehouse design for educational data mining	2016
[11]	Hybrid EA + BI for knowledge management in education	2019
[8]	Data warehouse with big data technology for higher education	2017
[16]	Predicting retention in online education	2005
[17]	CRISP-DM predictive models for student performance	2021
[9]	Adoption of a data warehouse in university management	2021
[7]	Challenges in developing a cost-effective DW in developing countries	2006
[5]	Conceptual data warehouse design	2000
[18]	BI model for evaluating national higher education	2020
[10]	Improving ETL and DW maintenance for HEIs	2009
[19]	Computing infrastructure for big data processing	2013
[2]	BI and analytics: big data to institutional impact	2012
[20]	Educational data mining: early survey (1995–2005)	2007
[4]	State of educational data mining and future directions	2009
[21]	Learning analytics framework validated with SVMs	2014
[22]	Big data in construction: methods applicable to HEI analytics	2016
[23]	Big social data analysis: methodological insights	2013
[24]	Ingesting a data lake into a NoSQL data warehouse	2021
[25]	Designing DW schemas from document-oriented databases	2019
[26]	Modeling language for geospatial document-oriented DWs	2023
[27]	Data mining with big data	2014
[6]	Model-driven approach for multidimensional DW models	2007

VI. RESULTS: THEMATIC SYNTHESIS

Analysis of the 24 included studies revealed five dominant themes relevant to ETL processes, data warehousing and analytics adoption in Higher Education Institutions (HEIs).

A. ETL PIPELINE AUTOMATION

Several studies emphasized the importance of automated ETL workflows that incorporate scheduling, error handling and metadata management. Mature HEIs typically employ structured ETL processes to ensure consistency and repeatability at scale [10]. In contrast, institutions in developing contexts frequently rely on manual scripts or ad-hoc procedures, limiting scalability and complicating maintenance [7]. Automated ETL pipelines were identified as essential prerequisites for reliable data integration and analytics readiness across HEI environments.

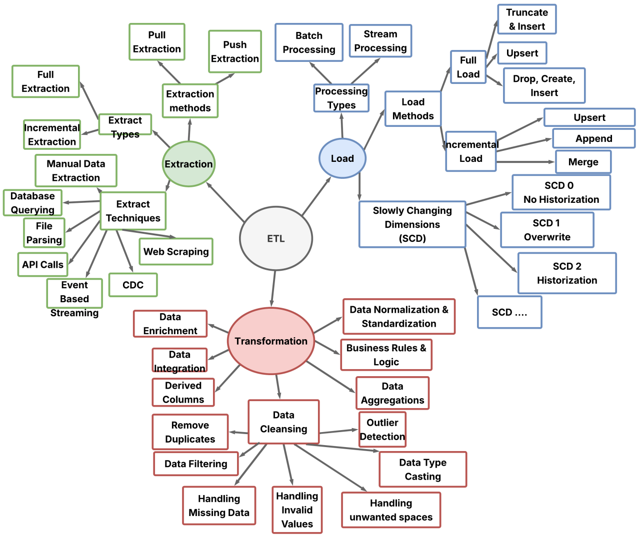

FIGURE 2: ETL

B. DATA WAREHOUSE MODELING APPROACHES

The literature identifies multiple modeling approaches most notably the multidimensional star schema, which remains the dominant architecture for analytical workloads due to its simplicity and query efficiency [5]. Model-driven approaches for deriving DW schemas were also discussed, demonstrating how automation can support efficient DW design in educational settings [6]. Hybrid architectures that combine enterprise frameworks and BI components offer additional flexibility for HEIs with evolving data needs [11].

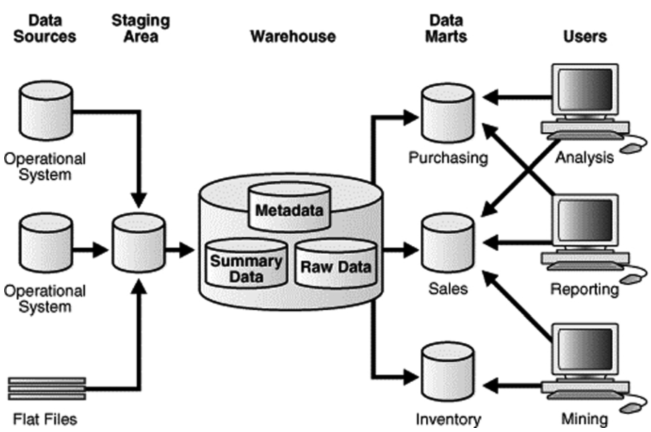

FIGURE 3: multidimensional star schema

C. DATA QUALITY AND GOVERNANCE

Data quality challenges including duplicated records, inconsistent formats and missing data were consistently recognized as barriers to analytics adoption. Studies stressed that reliable analytics depend on coordinated governance practices such as stewardship, standardized identifiers and validation rules [28]. Research focusing on HEIs in developing contexts also highlighted the prevalence of inconsistent data collection procedures and limited governance capacity, underscoring the need for institution-wide data quality initiatives [8].

D. PREDICTIVE ANALYTICS INTEGRATION

Studies from mature HEIs demonstrate active use of predictive analytics for student retention, performance forecasting and risk identification [4], [12]. Machine learning–driven approaches such as support vector machines and CRISP-DM workflows have shown effectiveness in analyzing educational datasets [17], [21]. However, African universities rarely implement these models due to foundational gaps in data engineering and DW infrastructure, which limit the availability of clean, longitudinal datasets necessary for predictive modeling [9].

E. BI DASHBOARDS AND DECISION SUPPORT

Business intelligence dashboards are widely recognized for enhancing operational visibility and supporting data-driven decision-making. Evidence shows that HEIs benefit from BI tools that consolidate institutional data into centralized dashboards for monitoring academic and administrative performance [11]. Although proprietary BI tools are common in global HEIs, open-source platforms provide viable pathways for low-cost adoption in resource-constrained environments [18]. These tools serve as an accessible entry point for institutions seeking to establish foundational decision-support capabilities.

VII. DISCUSSION

The findings reveal a substantial readiness gap between mature global ETL–DW ecosystems and the operational realities of many Ugandan HEIs. Studies from technologically advanced universities highlight the benefits of structured ETL automation, institutional data governance and enterprise BI frameworks [1], [2], [11]. These environments assume stable infrastructure, specialized technical personnel and established governance practices conditions that are often absent in Ugandan institutions.

Evidence from developing country contexts indicates that HEIs commonly rely on manual reporting, fragmented systems and limited data engineering capacity [7]–[9]. These constraints make direct adoption of global ETL–DW models unrealistic without adaptation. The literature instead supports staged modernization, beginning with improvements in data quality and standardization [28], followed by progressive automation of ETL workflows using modular or open-source tools [10], and ultimately the adoption of hybrid local–cloud architectures to balance infrastructural limitations with scalability.

Global HEIs also demonstrate widespread use of learning analytics and predictive modeling to support academic decision-making [4], [12]. However, African universities often lack the clean, integrated datasets necessary for such applications, reinforcing the need to strengthen foundational ETL and DW processes before advanced analytics can be effectively deployed.

VIII. CONCEPTUAL FRAMEWORK: MEDALLION ARCHITECTURE

The proposed conceptual framework is grounded in insights from the reviewed literature and tailored to the operational realities of Ugandan HEIs particularly Uganda Christian University. While global universities implement a range of data architectures, including traditional data warehouses, data lakes, lakehouses, and data meshes, not all are feasible in resource limited environments. Studies show that HEIs benefit most from architectures that combine structured ETL workflows, scalable storage and simplified analytics pipelines [2], [11].

Figure 4 illustrates a comparative view of common data architecture paradigms alongside the Medallion Architecture, which is highlighted as the most practical option for constrained institutions. Traditional approaches such as Inmon's 3NF enterprise warehouse and Kimball's dimensional modeling offer strong analytical consistency but require substantial integration effort and governance capacity [5], [6]. Data Vault frameworks provide flexibility for evolving institutional data but demand specialized skills and higher maintenance overhead [10].

In contrast, the Medallion Architecture organizes data into incremental quality layers **Bronze, Silver and Gold** which simplifies ETL design, supports modular automation and enables progressive data quality improvements. This staged transformation philosophy is consistent with best practices identified in low-resource HEI environments, where gradual modernization is preferred over large monolithic deployments [7], [8]. The architecture therefore offers a balanced pathway for institutions seeking to enhance data reliability, optimize reporting and prepare for advanced analytics without extensive infrastructure investments.

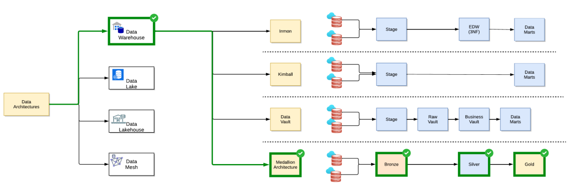

FIGURE 4: Medallion conceptual framework tailored for resource-constrained HEIs.

IX. LIMITATIONS

This systematic review was limited to studies indexed in SCOPUS and Web of Science. As a result, relevant regional research, institutional reports, these, and practitioner-oriented literature particularly from African HEIs may not have been captured. The included studies also varied considerably in scope and design, ranging from technical frameworks to case studies and conceptual analyses. Such heterogeneity made quantitative meta-analysis infeasible and required reliance on qualitative thematic synthesis. Several challenges reported in studies from developing country contexts, including limited documentation and sparse methodological detail [7], [9], may have influenced the depth of comparative interpretation.

In addition, several potentially relevant studies identified during screening were excluded because they were not indexed in SCOPUS or Web of Science. These sources (summarized in Table 2) offer useful practitioner insights but lack the peer-reviewed rigor required for inclusion in this SLR. Their exclusion highlights a structural gap in the visibility and dissemination of data warehousing and analytics research from African and developing country institutions.

TABLE 2: Relevant Studies Not Indexed in SCOPUS or Web of Science

Source	Focus / Contribution	Reason Not Included
CIO (2021) [29]	Need for data warehouses in African enterprises.	Grey literature; not peer-reviewed.
UFS (2023) [30]	Feasibility of DW for a tertiary institution.	Institutional report; not indexed.
Kibugu (2016) [31]	ETL-based DW implementation methodology.	PhD thesis; not indexed.
Setiyawati (2025) [32]	ETL for admissions analytics in HE.	Regional outlet; not indexed.
ResearchGate (2025) [33]	DW adoption case study.	Uploaded manuscript; no peer review.
Astera (2024) [34]	Industry perspective on DW needs.	Blog/industry source.
Gulu (2023) [35]	Research data management issues in Uganda.	Journal unspecified; not indexed.
Turyamureeba (2023) [36]	Analytics in education improvement.	Regional journal; not indexed.

X. FUTURE WORK

Future empirical work should pilot the proposed hybrid ETL–DW architecture across multiple Ugandan HEIs to evaluate measurable improvements in reporting latency, data quality and total cost of ownership. The review found that data quality and governance challenges are persistent in developing country HEIs [7], [9], suggesting that future research should also explore scalable governance models suited to resource constrained environments.

Given the infrastructural limitations observed in regional institutions [8], additional work is needed to design and test low-bandwidth synchronization mechanisms that can reliably support intermittent connectivity. As global HEIs increasingly adopt predictive analytics and machine learning for student success initiatives [4], [12], future research should investigate AI-assisted data cleaning and automated feature engineering techniques tailored to the noisy and incomplete datasets common in Ugandan HEIs. These studies should be prioritized.

XI. CONCLUSION

This systematic review synthesizes evidence on ETL processes, data warehousing architectures and analytics adoption in higher education to articulate a pragmatic, resource conscious modernization pathway for Ugandan HEIs. The findings demonstrate clear contrasts between global best practices characterized by automated ETL workflows, strong governance, and scalable cloud infrastructures [1], [2], [11] and the fragmented, manually driven environments common in developing contexts [7], [8].

A. SYNTHESIS OF FINDINGS

- **Technical maturity gap:** The literature confirms a substantial disparity between mature ETL–DW ecosystems and the realities of Ugandan HEIs, where manual processes dominate and limit analytical potential [9].
- **Data quality as foundational:** Reliable analytics require consistent identifiers, validation rules and stewardship practices a conclusion supported across DW and BI studies [28]. Without these, ETL pipelines incur recurring rework and unreliable outputs.
- **Architecture pragmatism:** Evidence supports hybrid local cloud architectures as feasible in low-resource environments, offering resilience and scalability while accommodating infrastructural constraints [7], [8].
- **Open-source feasibility:** Studies indicate that HEIs can meaningfully advance their data capabilities through modular, open-source tooling rather than high-cost proprietary platforms [10].
- **Human capital imperative:** Sustainable analytics ecosystems depend on staff training, governance capacity and change management, consistent with findings in BI adoption and knowledge management research [11].

B. OPERATIONAL RECOMMENDATIONS (PRIORITIZED)

1) **Immediate (0–3 weeks):** Establish standardized identifiers and basic validation rules; deploy a lightweight staging schema; initiate small ETL pilots in a single faculty. These steps address foundational data-quality issues noted in prior studies [28].
2) **Short term (3-6 weeks):** Introduce an ETL orchestrator (e.g., cron or Airflow) and implement standardized metadata conventions. Deploy an RDBMS-based DW and roll out initial BI dashboards, consistent with successful HEI deployments documented in the literature [8].
3) **Medium term (6-9 weeks):** Enable cloud syncing for archival and ML workloads; operationalize early-warning models for student risk prediction, reflecting practices observed in global HEIs [4], [12]. Formalize governance processes.
4) **Long term (9+ weeks):** Advance toward near-real-time analytics, integrate cross-institutional benchmarking and institutionalize analytics functions within governance structures.

C. RESEARCH CONTRIBUTIONS

This SLR contributes:

- A consolidated synthesis of ETL and DW practices relevant to HEIs operating in resource constrained contexts, addressing challenges identified in developing-country studies [7], [9].
- A practical hybrid conceptual framework informed by global BI and enterprise architecture evidence [2], [11].
- A prioritized roadmap and research agenda to guide empirical validation in Ugandan HEIs, aligned with staged modernization approaches recommended across the literature [8], [10].

Sustained institutional progress will require coordinated investment in governance, skills development and incremental technical deployments. Nevertheless, the potential benefits ranging from improved decision quality to enhanced student support and organizational resilience are substantial.

ACKNOWLEDGEMENTS

The authors thank colleagues at NextGen Data Architects for their technical guidance and express their sincere appreciation to Dr. Terhemba Michael-Ahile (PhD) for the supervision and scholarly support. The authors also acknowledge Uganda Christian University, Department of Computing, for their valuable contributions.

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