Data Processing Pipeline for Course-Level Outcome Analytics in Higher Education: Time-Based and Clustering-Based Hybrid Approaches

Besiki Tabatadze

PhD (Applied Mathematics), Professor, European University, Georgian American University, Tbilisi, Georgia.

Email: *tabatadze.besik@eu.edu.ge*

Sophio Khundaze

PhD, European University, Tbilisi, Georgia.

Email: *skhundadze@eu.edu.ge*

Abstract

One of the key tasks of quality assurance in higher education is the systematic monitoring of course-level outcomes and the adoption of appropriate decisions based on the analysis of these results. Although quality assurance standards and guidelines place strong emphasis on data-informed monitoring and the periodic review of programmes, practical analytical approaches applied at the course level often remain diverse and unevenly formalized. This situation is largely influenced by the institutional autonomy granted to higher education institutions, which results in diverse practices across institutions.

The aim of this paper is to review and comparatively analyze contemporary data-informed and analytics-based approaches to course-level quality assurance. The study is based on a systematic examination of existing approaches, including the analysis of aggregated assessment data, the use of learning analytics and educational data mining, as well as the role of explainable analytics in supporting academic and managerial decision making. The review is complemented by a practice-oriented example based on real data, which examines the longitudinal analysis of assessment outcomes for the same course over multiple academic years.

The findings indicate that the analysis of grade distributions and performance dynamics can be effectively used to identify the need for improvements in course content, teaching methods, allocation of instructional time and assessment systems. The paper highlights the specific characteristics of different approaches, their strengths and limitations, and emphasizes the importance of using modern technologies to support course-level quality assurance processes.

Keywords: Quality Assurance in Higher Education, Learning Analytics, Data Processing, Hierarchical Clustering, Unsupervised Learning, Grade Distribution Analysis

Introduction

Quality assurance has long been recognized as one of the central issues in higher education and encompasses multiple dimensions related to teaching, learning, assessment, institutional effectiveness, and other processes taking place within higher education institutions (HEIs). The definition of quality assurance in HEIs emphasizes its multidimensional and context-dependent nature, which includes the transformation and enhancement of teaching processes in order to ensure learning outcomes (Harvey & Green, 1993).

Within this process, quality assurance at the course level plays a critical role, as the objectives of individual courses are aligned with the objectives of the corresponding academic program, which in turn reflect institutional goals, in accordance with the principles of outcomes-based education (Biggs et al., 2022). Thus, the learning outcomes achieved by students within individual courses determine the attainment of program-level outcomes, which consequently contributes positively to the overall quality development of the HEI. It can be argued that outcomes achieved at the course level represent the primary interface between institutional objectives and students' learning experiences.

The Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG) place strong emphasis on the continuous monitoring, periodic review, and evidence-based improvement of study programmes and courses (European Association for Quality Assurance in Higher Education [ENQA], 2015). At the same time, ESG does not prescribe specific analytical methods for evaluating course-level outcomes, which has led to the emergence of diverse practices and approaches to the analysis of course results across higher education institutions. These approaches differ in terms of the types of data used, the depth of analysis, and their intended purposes and modes of interpretation, thereby creating a clear need for their systematic examination and comparative analysis.

Proper alignment between course learning outcomes, subject content, teaching activities, and assessment methods is a fundamental prerequisite for quality learning (Biggs et al., 2022). Although the aggregated assessment results (grades) obtained by students in a course do not fully capture the quality of teaching and learning, the thoughtful and contextualized analysis of these outcomes plays an important role in supporting broader and continuous quality assurance processes (Boretz, 2004). Moreover, the systematic analysis of assessment results can inform meaningful adjustments in course design and implementation.

Data-informed decision making has gained increasing importance in higher education governance and curriculum development. Research indicates that the effective use of data can contribute to improvements in teaching and learning processes, provided that data are interpreted within appropriate pedagogical and organizational contexts (Schildkamp & Kuiper, 2010; Webber & Zheng, 2020). Advances in learning analytics, educational data mining, and related technologies have further expanded the possibilities for analyzing student achievement and learning processes (Shafiq et al., 2022). In parallel, the digitalization of educational processes and the development of data processing and analytical technologies have significantly broadened opportunities for enhancing the quality of teaching and learning (Martin et al., 2020).

At the course level, observing and analyzing the numerical distribution of students' assessment outcomes can serve as an important source of information for evaluating the effectiveness of individual courses (Rexwinkel et al., 2013). Recent practice-oriented studies further demonstrate how the use of data and data visualization techniques within learning management systems can enhance the interpretability of course-level outcomes and support informed academic decision making (Tabatadze, 2023; Tabatadze & Sokhadze, 2023).

In this context, the aim of the present paper is to review and comparatively analyze contemporary data-informed and analytics-based approaches to course-level quality assurance in higher education. The study seeks to demonstrate how explainable and accessible analytical methods can be employed to support effective course review processes and continuous quality improvement.

Review of Assessment-Based Approaches to Course-Level Outcome Analysis

The present study is based on aggregated assessment data, specifically the quantitative distribution of final grades (A - F) awarded to students in individual courses. The paper examines the types of analytical approaches and evaluative interpretations that can be applied on the basis of course-level outcomes after course completion and compares these approaches with one another. Although this type of data does not allow for a detailed analysis of individual students' learning trajectories, it nevertheless represents an important source for identifying systemic patterns and potential issues at the course level (Schildkamp & Kuiper, 2010; Rexwinkel et al., 2013). Such data can be conceptualized as outcome-level distribution data, which are widely used in quality assurance practices to evaluate the effectiveness of individual courses (Boretz, 2004; Rexwinkel et al., 2013).

Based on the assessment outcomes achieved by students within a specific course, a variety of approaches can be employed to analyze course-level results in support of quality assurance processes. These approaches differ in terms of analytical depth, temporal scope, and interpretative focus. Some methods rely on descriptive statistical analysis of grade distributions, while others adopt comparative or longitudinal approaches, enabling the identification of trends, changes, and potential anomalies across different academic years and student cohorts (Schildkamp & Kuiper, 2010; Rexwinkel et al., 2013). In addition, so-called hybrid approaches are increasingly used, integrating elements of learning analytics, data visualization, and rule-based interpretation in order to enhance the explainability and practical usability of analytical results for academic staff and decision makers (Martin et al., 2020; Tabatadze, 2023; Tabatadze & Sokhadze, 2023).

Within the context of course-level outcome analysis, several widely used approaches can be identified. These include descriptive statistical analysis of grade distributions, comparative analysis across courses or student cohorts, longitudinal analysis of course outcomes over multiple academic years, threshold- and rule-based evaluation approaches, as well as analytics-driven methods that employ statistical techniques, data visualization tools, and contemporary technological capabilities, including machine learning models (Schildkamp & Kuiper, 2010; Rexwinkel et al., 2013; Martin et al., 2020; Tabatadze, 2023; Tabatadze & Sokhadze, 2023). These approaches differ in terms of analytical depth, interpretative scope, and their practical applicability to course-level quality assurance processes.

Descriptive Grade Distribution Approaches

Course-level outcome analysis frequently relies on descriptive representations of assessment results, such as the distribution of grades on an A–F scale and pass/fail indicators. Such outcome-level distribution data are widely used as an analytical tool that enables the timely interpretation of the overall performance profile of a course and the identification of potentially critical system-wide signals. It is noteworthy that, in institutional practice, grade distribution analysis is often employed as an initial stage of quality assurance processes, particularly when the objective is to monitor course outcomes and to support the early detection of problematic trends (Boretz, 2004; Rexwinkel et al., 2013; Schildkamp & Kuiper, 2010).

Threshold- and Indicator-Based Quality Signals

In practice, threshold- and indicator-based approaches are widely applied to identify potential quality issues at the course level. Studies and quality assurance documentation frequently refer to indicators such as a high proportion of low grades (e.g., F) or the cumulative share of weak outcomes (D+E+F), which may signal problems related to assessment design, student workload, or teaching methods. At the same time, an excessive concentration of high grades (A+B) is often discussed as a potential indicator of grade inflation. Importantly, such thresholds are not interpreted as rigid rules; rather, they are commonly used in quality assurance practice as heuristic signals that require further analysis and contextual interpretation (Boretz, 2004; Rexwinkel et al., 2013; Schildkamp & Kuiper, 2010).

Longitudinal and Trend-Based Approaches

In course-level quality evaluation, particular importance is attributed to longitudinal and trend-based approaches that rely on the analysis of outcomes from the same course across multiple academic years. The use of multi-year data makes it possible to identify stable trends, recurring deviations, and so-called structural problems that often remain invisible when analysis is based on a single cohort or academic year. In the literature, such dynamics are frequently described in terms of a critical trajectory, indicating systematic deterioration or improvement in course outcomes over a defined period of time (Rexwinkel et al., 2013; Schildkamp & Kuiper, 2010).

Statistical Significance-Based Approaches

In some cases, course-level outcome analysis is grounded in methods based on statistical significance testing. Within this context, techniques such as the χ^2 test are employed to assess differences between grade distributions, while effect size indicators are used to capture the practical significance of observed changes. Such approaches are particularly important when the objective is to distinguish random fluctuations from genuine, systematic changes in course outcomes and to strengthen the scientific robustness and credibility of analytical conclusions (Rexwinkel et al., 2013; Schildkamp & Kuiper, 2010).

Analytics- and Rule-Based Approaches (Explainable)

In recent years, analytics- and rule-based approaches grounded in the technological processing of educational data have increasingly been applied to enhance the transparency and interpretability of course-level outcome analysis. Within this context, machine learning models are commonly used for clustering tasks, enabling courses to be grouped according to similarities in outcome distributions and facilitating the identification of shared patterns across courses. At the same time, the literature emphasizes that more complex models, such as deep learning algorithms, despite their strong predictive capabilities, are less practical for course-level quality assurance due to their limited interpretability and low level of explainability. Consequently, greater emphasis is placed on simpler and more interpretable approaches, including unsupervised clustering techniques and rule-based decision logic, which are more closely aligned with the practical requirements of quality assurance processes and support explainable, data-informed decision making (Schildkamp & Kuiper, 2010; Martin et al., 2020; Shafiq et al., 2022).

Hybrid Approaches in Course-Level Quality Assurance

In quality assurance practice, course-level outcome analysis is rarely based on a single, isolated analytical approach. Instead, so-called hybrid approaches are commonly applied, combining elements of two or more complementary methods selected in accordance with specific analytical objectives and contextual conditions. In practice, such combinations may include, for example, descriptive analysis of grade distributions together with threshold-based indicators, or longitudinal trend analysis combined with tests of statistical significance, while in some cases a broader analytical framework may be employed. This selective integration enables stronger interpretation of results, reduces the impact of limitations inherent in individual methods, and supports more balanced and context-sensitive conclusions based on outcome-level data. Consequently, hybrid approaches represent a flexible and practice-oriented instrument for course-level quality assurance processes.

The approaches discussed above illustrate the diversity of analytical perspectives that can be applied to course-level outcome data. While each method emphasizes different aspects of course performance, their combined use in practice enables a more comprehensive and nuanced interpretation of quality-related signals. Of particular interest, therefore, is not the comparison of individual analytical approaches in isolation, but the examination of selected combinations of these approaches and the outcomes they produce. From a research perspective, it is especially important to assess how the use of two or three complementary methods in combination influences the interpretation, robustness, and practical usability of conclusions drawn from course-level quality assurance analyses.

Two Hybrid Analytical Approaches

An important area of research concerns the examination of different hybrid analytical approaches and their comparative analysis within the context of course outcome–based quality assurance. Within the framework of the present paper, two hybrid approaches are examined, which are deliberately formulated to reflect two distinct yet complementary paradigms of data-informed quality assurance. The first approach is based on observing students' achieved outcomes over time and focuses on identifying the stability of course results and sustainable trends across multiple academic years. The second approach, in contrast to the first, concentrates on the analysis of single-semester data and employs analytics-based machine learning techniques, specifically clustering, to identify similarities and differences in outcomes across courses.

These two hybrid approaches are not viewed as mutually exclusive or competing alternatives. Rather, they are presented as analytically distinct frameworks that support quality assurance processes in different contexts. The time-based approach is particularly effective for identifying structural and recurring issues, whereas the clustering-based analytical approach is more suitable for rapid, data-driven interpretation in situations where only single-semester data are available.

Within the scope of the study, each hybrid approach is examined separately, taking into account its constituent analytical elements, underlying logic of application, and interpretative capacity. This is followed by a comparative analysis focusing on relevant criteria applied in quality assurance processes. This comparison provides the foundation for the subsequent empirical analysis, in which both hybrid approaches are applied to real-world data.

Time-Based Hybrid Analytical Approach

The time-based hybrid analytical approach is grounded in the observation of course outcomes over time and the analysis of data accumulated across multiple academic years. This approach constitutes a combination of descriptive analysis of grade distributions, threshold- and indicator-based evaluation methods, and longitudinal trend analysis, thereby forming a hybrid analytical framework. The primary objective of this approach is not the evaluation of a single semester or cohort, but the identification of dynamics, stability, and recurring patterns in course outcomes over time. Such a perspective is particularly important in quality assurance processes, where single-point data often fail to capture systemic issues or long-term changes.

This hybrid analytical approach integrates the following analytical components:

- Descriptive analysis of grade distributions;
- Threshold- and indicator-based evaluation approaches;
- Longitudinal and trend-based analytical approaches.

At the first stage, descriptive analysis of grade distributions is applied to provide an overall profile of course outcomes for each academic year. This analysis is complemented by threshold- and indicator-based evaluation, which enables the identification of potentially critical signals, such as changes in the proportion of low or high grades over time.

At the second stage, longitudinal and trend-based analysis is conducted, in which course outcomes are examined as a time series. This makes it possible to identify stable trends, recurring deviations, and so-called structural problems that may indicate imbalances in course content, teaching methods, or assessment design. Particular attention is given to dynamics described as a critical trajectory, referring to a consistent deterioration or improvement in outcomes over a defined period.

The main strength of this hybrid approach lies in its ability to support contextualized and robust interpretation of results. The use of multi-year data reduces the influence of random fluctuations and enhances the reliability of analytical conclusions. At the same time, one of its limitations is its reliance on historical data, which makes it less effective in cases where a course is newly introduced or has undergone recent substantive changes.

Overall, the time-based hybrid analytical approach represents an effective instrument for the systematic evaluation of course outcomes and is particularly well suited to quality assurance processes oriented toward long-term development and the planning of structural improvements.

Clustering-Based Hybrid Analytical Approach

The clustering-based hybrid analytical approach focuses on the structural analysis of course outcomes within a single academic period and aims to identify similarities and differences between courses through outcome-based clustering of data. In contrast to time-based approaches, this analytical framework is designed for contexts in which longitudinal data are not available or where the primary objective is to support rapid and comparative interpretation of course-level results. The approach integrates descriptive and rule-based evaluation with analytics-oriented methods, resulting in a clustering-centered hybrid analytical configuration.

This hybrid analytical approach integrates the following analytical components:

- descriptive analysis of grade distributions;
- threshold- and indicator-based evaluation approaches;
- analytics- and clustering-based analytical methods.

At the initial stage, descriptive analysis of grade distributions is applied, whereby outcome profiles for each course are constructed using A–F grade scales, pass/fail indicators, and other relevant metrics. This stage ensures a structured representation of outcome-level data and establishes a common analytical basis for subsequent comparison.

At the next stage, threshold- and indicator-based evaluation is conducted, enabling the identification of potentially critical quality signals, such as a high proportion of weak outcomes or an excessive concentration of high grades. These indicators are not interpreted as rigid rules, but rather are used as heuristic reference points that guide further interpretation.

The central element of this hybrid approach is clustering based on machine learning techniques, which aims to group courses according to similarities in their outcome distributions. The application of unsupervised clustering methods makes it possible to reveal latent structural patterns across courses and to form groups with comparable performance profiles. At the same time, particular emphasis is placed on explainable clustering solutions, which ensure the transparency and practical usability of analytical results for academic staff and quality assurance units.

The main strength of the clustering-based hybrid analytical approach lies in its ability to support rapid, data-informed interpretation in contexts where only single-semester data are available. The combination of descriptive analysis, indicator-based evaluation, and explainable machine learning facilitates the identification of structural similarities between courses and the detection of potentially problematic groups. However, a key limitation of this approach is the absence of a temporal dimension, which restricts the assessment of result stability and long-term trends.

Overall, the clustering-based hybrid analytical approach represents a flexible and practice-oriented instrument for course-outcome-based quality assurance processes, particularly in contexts that require timely analytical responses and the explainable use of data-driven methods.

The approaches described represent two distinct yet complementary analytical configurations for assessment-based quality assurance and reflect different logics and contexts of data-informed analysis. In this regard, a comparative examination of these approaches is of particular interest.

The time-based hybrid approach (1–2–3)[1] supports a dynamic and stable evaluation of course outcomes and is particularly effective in identifying structural and recurring issues. In contrast, the clustering-based hybrid approach (1–2–5)[2] is oriented toward simultaneous structural comparison and enables rapid, data-driven interpretation in contexts where only single-semester data are available.

The analysis is conducted using real assessment data, which allows for the evaluation of the practical effectiveness of both hybrid approaches within an authentic educational context. The use of empirical data enables the translation of theoretically described analytical differences into practically interpretable results and highlights the specific strengths and limitations associated with the application of each approach.

Empirical Application of Hybrid Analytical Approaches

To demonstrate the practical applicability of the proposed hybrid analytical approaches, both methods are implemented in this study using the same real, aggregated assessment data. The dataset covers course-level outcomes from the Fall semesters of three consecutive academic years (2022–2023, 2023–2024, and 2024–2025). The purpose of the empirical analysis is not to evaluate individual instructors or students, but rather to illustrate how the analysis of grade distributions at the course level can support data-informed quality assurance processes.

The data used in the analysis include both percentage-based and absolute distributions of final student grades (A–F) by course, as well as the total number of students enrolled in each course. To avoid unstable or misleading interpretations, the core analytical conclusions are based only on courses with a minimum enrollment of N students (in this case, N = 10). Courses with

[1] (1) Descriptive grade distribution analysis;
(2) Threshold- and indicator-based evaluation approaches;
(3) Longitudinal and trend-based analysis;.

[2] (1) Descriptive grade distribution analysis;
(2) Threshold- and indicator-based evaluation approaches;
(5) Analytics- and clustering-based methods

small cohort sizes are treated as preliminary signals that require additional contextual evaluation and are not used for drawing final conclusions.

The dataset used in the study comprises 10 courses from the Fall 2022–2023 semester, 15 courses from the Fall 2023–2024 semester, and 17 courses from the Fall 2024–2025 semester. Among these, 7 courses were offered consistently across all three academic years.

Table 1. Course-level grade distributions (A–F), Fall 2022–2023.

Subject	Grades						
	A	B	C	D	E	F	Total
Computer Graphics Tools (Photoshop)	28.6% (4)	21.4% (3)	14.3% (2)	0% (0)	7.1% (1)	28.6% (4)	100% (14)
Computer Hardware	3.2% (1)	3.2% (1)	29.0% (9)	32.3% (10)	19.4% (6)	12.9% (4)	100% (31)
Computer Networks	0% (0)	0% (0)	0% (0)	36.4% (4)	36.4% (4)	27.3% (3)	100% (11)
Computer Skills	0% (0)	7.7% (1)	7.7% (1)	23.1% (3)	30.8% (4)	30.8% (4)	100% (13)
Database Management Systems (MS SQL Server)	0% (0)	0% (0)	13.3% (2)	46.7% (7)	20.0% (3)	20.0% (3)	100% (15)
English Language B1.1	0% (0)	0% (0)	0% (0)	30.8% (4)	30.8% (4)	38.5% (5)	100% (13)
Fundamentals of Web Design	9.7% (3)	9.7% (3)	19.4% (6)	19.4% (6)	16.1% (5)	25.8% (8)	100% (31)
Introduction to Programming (Python-Based)	7.7% (1)	30.8% (4)	23.1% (3)	7.7% (1)	0% (0)	30.8% (4)	100% (13)
Linear Algebra and Analytic Geometry	0% (0)	0% (0)	5.6% (1)	33.3% (6)	22.2% (4)	38.9% (7)	100% (18)
Object-Oriented Programming (C++)	0% (0)	7.1% (1)	0% (0)	28.6% (4)	28.6% (4)	35.7% (5)	100% (14)

Table 2. Course-level grade distributions (A–F), Fall 2023–2024.

Subject	Grades						
	A	B	C	D	E	F	Total
Academic Writing	0% (0)	20% (2)	20% (2)	0% (0)	0% (0)	60% (6)	100% (10)
Applied Programming	0% (0)	0% (0)	27.3% (3)	45.5% (5)	0% (0)	27.3% (3)	100% (11)
Calculus	10% (2)	15% (3)	10% (2)	35% (7)	15% (3)	15% (3)	100% (20)
Computer Graphics Tools (Photoshop)	2% (1)	7.8% (4)	7.8% (4)	21.6% (11)	15.7% (8)	45.1% (23)	100% (51)
Computer Hardware	0% (0)	0% (0)	4% (2)	10% (5)	14% (7)	72% (36)	100% (50)
Computer Networks	0% (0)	0% (0)	0% (0)	13.6% (3)	45.5% (10)	40.9% (9)	100% (22)
Computer Skills	0% (0)	7.7% (4)	17.3% (9)	25% (13)	23.1% (12)	26.9% (14)	100% (52)
English for Informatics	18.2% (2)	9.1% (1)	9.1% (1)	36.4% (4)	0% (0)	27.3% (3)	100% (11)
English Language B2.1	0% (0)	0% (0)	6.7% (1)	20% (3)	40% (6)	33.3% (5)	100% (15)
English Language B2.2	10% (1)	0% (0)	40% (4)	30% (3)	0% (0)	20% (2)	100% (10)
Fundamentals of Web Design	4.2% (2)	2.1% (1)	8.3% (4)	10.4% (5)	12.5% (6)	62.5% (30)	100% (48)
Introduction to Programming (Python-Based)	5.8% (3)	9.6% (5)	26.9% (14)	23.1% (12)	7.7% (4)	26.9% (14)	100% (52)
Object-Oriented Programming (C++)	9.5% (2)	4.8% (1)	4.8% (1)	23.8% (5)	38.1% (8)	19% (4)	100% (21)
Probability Theory and Mathematical Statistics	0% (0)	0% (0)	7.1% (1)	57.1% (8)	14.3% (2)	21.4% (3)	100% (14)
Web Programming (Server-Side)	7.1% (1)	7.1% (1)	7.1% (1)	14.3% (2)	42.9% (6)	21.4% (3)	100% (14)

Table 3. Course-level grade distributions (A–F), Fall 2024–2025.

Subject	Grades						
	A	B	C	D	E	F	Total
Applied Programming	0% (0)	0% (0)	11.1% (2)	22.2% (4)	27.8% (5)	38.9% (7)	100% (18)
Calculus	14.3% (2)	35.7% (5)	21.4% (3)	7.1% (1)	0% (0)	21.4% (3)	100% (14)
Computer Graphics Tools (Photoshop)	4% (1)	16% (4)	8% (2)	12% (3)	0% (0)	60% (15)	100% (25)
Computer Hardware	2.9% (1)	8.8% (3)	5.9% (2)	14.7% (5)	0% (0)	67.6% (23)	100% (34)
Computer Networks	0% (0)	0% (0)	5.3% (1)	21.1% (4)	21.1% (4)	52.6% (10)	100% (19)
Computer Skills	0% (0)	5.9% (1)	17.6% (3)	23.5% (4)	5.9% (1)	47.1% (8)	100% (17)
Database Management Systems (MS SQL Server)	7.7% (2)	7.7% (2)	11.5% (3)	30.8% (8)	11.5% (3)	30.8% (8)	100% (26)
English for Informatics	5% (1)	15% (3)	35% (7)	30% (6)	5% (1)	10% (2)	100% (20)
Fundamentals of Artificial Intelligence	0% (0)	0% (0)	0% (0)	16.7% (3)	55.6% (10)	27.8% (5)	100% (18)
Fundamentals of Web Design	0% (0)	0% (0)	4.2% (1)	12.5% (3)	16.7% (4)	66.7% (16)	100% (24)
Introduction to Programming (Python-Based)	6.2% (1)	18.8% (3)	6.2% (1)	12.5% (2)	6.2% (1)	50% (8)	100% (16)
Mathematical Modeling	14.3% (4)	14.3% (4)	14.3% (4)	25% (7)	0% (0)	32.1% (9)	100% (28)
Mobile Application Design and Development	0% (0)	20% (2)	10% (1)	30% (3)	0% (0)	40% (4)	100% (10)
Object-Oriented Programming (C++)	17.6% (3)	11.8% (2)	17.6% (3)	5.9% (1)	17.6% (3)	29.4% (5)	100% (17)
Probability Theory and Mathematical Statistics	0% (0)	26.3% (5)	10.5% (2)	31.6% (6)	0% (0)	31.6% (6)	100% (19)
Programming on the JVM Platform I	16.7% (2)	8.3% (1)	25% (3)	25% (3)	8.3% (1)	16.7% (2)	100% (12)
Web Programming (Server-Side)	6.2% (1)	6.2% (1)	6.2% (1)	18.8% (3)	18.8% (3)	43.8% (7)	100% (16)

Practical Application of the Time-Based Hybrid Analytical Approach to Course-Level Data

The time-based hybrid analytical approach examines course-level outcomes jointly across three academic years. The primary objective of the analysis is to assess the extent to which course outcomes remain stable over time. In this context, particular attention is given to specific segments of grade distributions that are interpreted as indicators of low and high academic outcomes. These indicators are not defined through a single fixed combination but are applied in different aggregated forms, depending on the analytical objective and the contextual characteristics of each course.

In the analysis of low outcomes, both the individual grade F and its extended aggregations (E–F or D–E–F) may be employed, reflecting different levels of interpretative strictness. For instance, focusing solely on grade F highlights cases of extreme failure, whereas the D–E–F aggregation provides a broader picture of the proportion of students who failed to meet minimum course requirements or achieved results at a marginal level. This distinction is important, as a given course may not exhibit a high share of F grades while still being characterized by a substantial concentration of D and E grades near the passing threshold.

Similarly, the analysis of high outcomes is not limited to grade A alone. In practice, both A and the aggregated A–B indicators are used, as they capture different aspects of high achievement distribution. An analysis based exclusively on grade A highlights exceptional performance, whereas the A–B aggregation provides a more stable and less sensitive indicator that better reflects overall academic success at the course level.

Within the framework of this study, grade distribution analysis was conducted using A–B (high outcomes) and E–F (low outcomes) indicators, with 30% and 40% aggregation thresholds, respectively, applied as critical cut-off values. These thresholds are treated as clear and interpretable signals for identifying structural characteristics in course-level assessment profiles.

Courses were identified in which the share of E–F grades reached or exceeded 40% in all three academic years. Such recurrence indicates that a high concentration of low outcomes does not represent a one-off anomaly but rather reflects a stable, time-consistent pattern. In these courses, the E–F share consistently reaches or exceeds the 40% threshold across all three academic years, pointing to systemic challenges related to course content difficulty, assessment design, or instructional workload. These courses are classified as cases of concern and represent the strongest signals identified through the time-based hybrid analytical approach.

Table 4. Courses with recurring low-outcome signals (E–F ≥ 40%)

Subject	E–F Grades		
	E–F (2022–2023)	E–F (2023–2024)	E–F (2024–2025)
Computer Networks	63.7%	86.4%	73.7%
Computer Skills	61.6%	50.0%	53.0%
Fundamentals of Web Design	41.9%	75.0%	83.4%
Object-Oriented Programming (C++)	64.3%	57.1%	47.0%

In addition, the share of A–B grades was analyzed using a 30% threshold. No course was found to exhibit a recurring A–B share at or above this threshold across all three academic years. In line with the logic of the approach, this indicates that, within the analyzed dataset, concentrations of high outcomes, despite notable increases observed in individual years do not demonstrate temporal stability and therefore do not constitute a systemic pattern. Accordingly, signals derived from the A–B indicator are interpreted as single-year or episodic phenomena rather than as structural characteristics at the course level.

Finally, the application of the time-based hybrid analytical approach demonstrates that, despite the availability of relatively extensive data across three academic years (10 courses in 2022–2023, 15 courses in 2023–2024, and 17 courses in 2024–2025), only 7 courses were suitable for longitudinal analysis, as they were offered consistently across all three years. Among these, only 4 courses exhibited recurring signals of concern, while the remaining courses fell outside the scope of detailed analysis under this approach. This finding indicates that the time-based hybrid analytical approach is effective in identifying stable and clearly defined problematic trends, yet its analytical coverage is inherently limited. Consequently, a more comprehensive and fine-grained understanding of course-level quality requires the application of additional analytical approaches alongside time-based analysis.

Practical Application of the Clustering-Based Hybrid Analytical Approach to Course-Level Data

The clustering-based hybrid analytical approach is grounded in a distinct analytical logic and aims to identify structural similarities and differences among courses within the scope of single-semester data. This approach is particularly effective in cases where a subset of courses does not meet the criterion of multi-year recurrence and therefore cannot be incorporated into time-based analytical frameworks.

Within this approach, each course is treated as a multidimensional object described by aggregated characteristics of grade distributions (e.g., proportions of high grades (A–B) and low grades (E–F); the inclusion of intermediate grade distributions is also possible). The objective of clustering is to group courses that occupy similar positions in the structure of their assessment profiles. This approach does not predefine problematic or high-performing cases; rather, it provides a basis for their identification through comparative analysis across courses and interpretation of the internal structure of the resulting clusters.

Relative analysis of courses within the space of assessment profiles compensates for the limitations of time-based analyses that arise from requirements of temporal recurrence. As a result, this approach functions as a complementary and more sensitive analytical tool, enabling the identification of structural patterns within a single-semester perspective, including courses that fall outside the scope of longitudinal analysis.

Based on the resulting clusters, courses can be subjected to substantive interpretation as well as grouped according to academic fields. In addition, similarities in assessment practices among instructors, the use of comparable assessment systems across courses, or other recurring approaches within the teaching and learning process may be identified.

Within the scope of the study, the implementation of the clustering-based hybrid analytical approach employed an agglomerative hierarchical clustering algorithm. This algorithm was selected due to its interpretability, its effective performance on small-scale datasets, and the absence of a requirement to predefine the number of clusters, which is particularly important for the relative analysis of assessment profiles at the course level. The hierarchical structure enables similarities and differences among courses to be assessed in a stepwise manner and visually represented within the assessment profile space.

It should be noted that the proposed analytical framework is not tied to a single clustering algorithm; depending on the research objectives, alternative methods such as k-means, DBSCAN, or other clustering algorithms may also be employed. The choice of algorithm depends on the data structure, the number of courses, and the interpretative goals of the analysis.

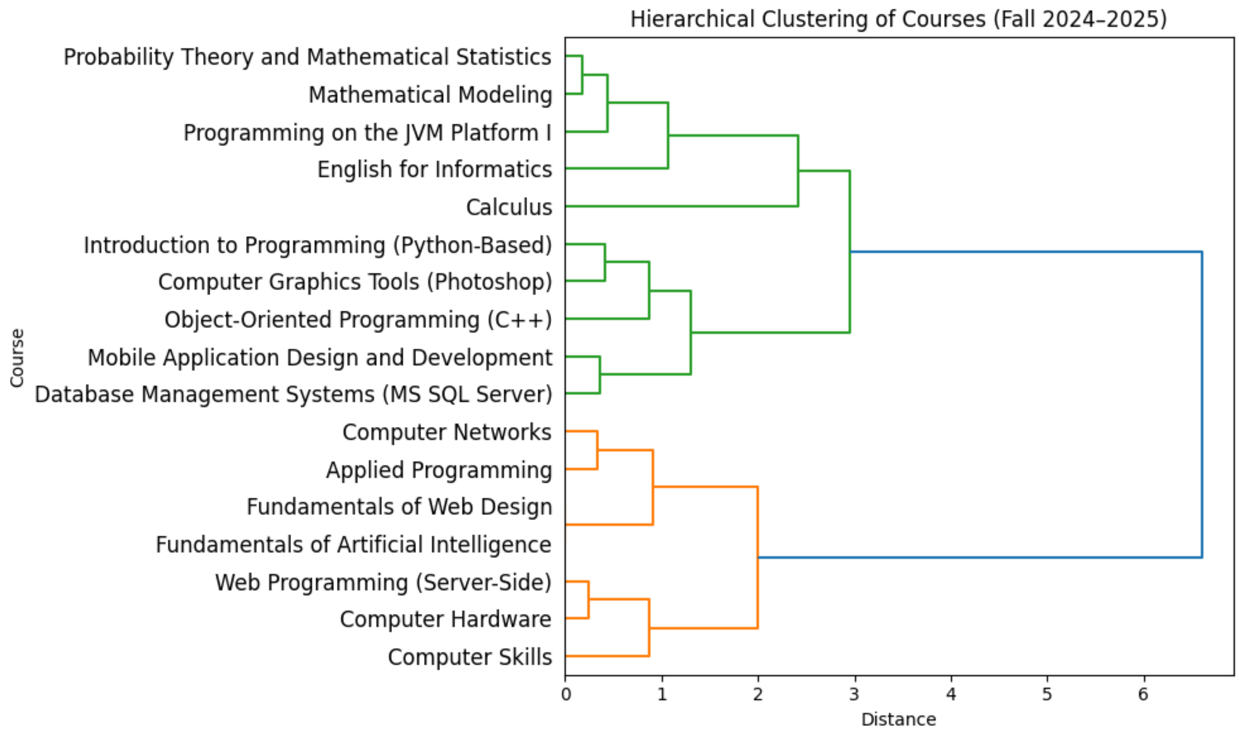
The clustering-based hybrid analytical approach was applied within a single-semester framework and is based on course-level assessment data obtained from the Fall semester of the 2024–2025 academic year. Each course is represented as a two-dimensional object within the assessment profile space, using aggregated proportions of high outcomes (A–B) and low outcomes (E–F). This representation allows for the simultaneous assessment of both academic achievement and academic difficulty at the course level.

To assess the degree of similarity among courses, Euclidean distance was employed, while Ward's linkage method was used for cluster formation, as it minimizes within-cluster variance and ensures the derivation of more stable and interpretable clusters. The implementation of the method was carried out on the Google Colab platform, which ensures accessibility of the computational environment, reproducibility of results, and transparency of the tools employed. Data analysis and clustering were performed using the Python programming language. At different stages of the analytical process, the following libraries were utilized:

- ✓ pandas — for loading and processing aggregated course-level assessment data;
- ✓ numpy — for numerical operations and vector representations;
- ✓ scikit-learn — for distance computation and supporting analytical functions;
- ✓ scipy — for the implementation of the agglomerative hierarchical clustering algorithm;
- ✓ matplotlib — for dendrogram visualization.

To provide a visual representation of the clustering results, a hierarchical dendrogram was constructed, illustrating similarities and differences among courses within the assessment profile space. The dendrogram enables stepwise observation of the cluster formation process and facilitates the identification of the structural relationships among courses within a single-semester perspective.

Figure 1. Hierarchical clustering dendrogram of courses based on aggregated grade distribution profiles (A–B and E–F ratios).



Based on the dendrogram, courses were ordered according to hierarchical similarity and transferred into a tabular format, which facilitates clearer interpretation of the clusters and comparative analysis. The table reflects the positioning of courses in accordance with the structure of the dendrogram.

Table 5. Course-level grade distribution profiles ordered according to hierarchical clustering results.

Subject	Grades						
	A	B	C	D	E	F	Total
Cluster 1							
Probability Theory and Mathematical Statistics	0% (0)	26.3% (5)	10.5% (2)	31.6% (6)	0% (0)	31.6% (6)	100% (19)
Mathematical Modeling	14.3% (4)	14.3% (4)	14.3% (4)	25% (7)	0% (0)	32.1% (9)	100% (28)
Programming on the JVM Platform I	16.7% (2)	8.3% (1)	25% (3)	25% (3)	8.3% (1)	16.7% (2)	100% (12)
English for Informatics	5% (1)	15% (3)	35% (7)	30% (6)	5% (1)	10% (2)	100% (20)
Calculus	14.3% (2)	35.7% (5)	21.4% (3)	7.1% (1)	0% (0)	21.4% (3)	100% (14)
Cluster 2							
Introduction to Programming (Python-Based)	6.2% (1)	18.8% (3)	6.2% (1)	12.5% (2)	6.2% (1)	50% (8)	100% (16)
Computer Graphics Tools (Photoshop)	4% (1)	16% (4)	8% (2)	12% (3)	0% (0)	60% (15)	100% (25)
Object-Oriented Programming (C++)	17.6% (3)	11.8% (2)	17.6% (3)	5.9% (1)	17.6% (3)	29.4% (5)	100% (17)
Mobile Application Design and Development	0% (0)	20% (2)	10% (1)	30% (3)	0% (0)	40% (4)	100% (10)
Database Management Systems (MS SQL Server)	7.7% (2)	7.7% (2)	11.5% (3)	30.8% (8)	11.5% (3)	30.8% (8)	100% (26)

Clauter 3							
Computer Hardware	2.9% (1)	8.8% (3)	5.9% (2)	14.7% (5)	0% (0)	67.6% (23)	100% (34)
Applied Programming	0% (0)	0% (0)	11.1% (2)	22.2% (4)	27.8% (5)	38.9% (7)	100% (18)
Fundamentals of Web Design	0% (0)	0% (0)	4.2% (1)	12.5% (3)	16.7% (4)	66.7% (16)	100% (24)
Fundamentals of Artificial Intelligence	0% (0)	0% (0)	0% (0)	16.7% (3)	55.6% (10)	27.8% (5)	100% (18)
Web Programming (Server-Side)	6.2% (1)	6.2% (1)	6.2% (1)	18.8% (3)	18.8% (3)	43.8% (7)	100% (16)
Computer Networks	0% (0)	0% (0)	5.3% (1)	21.1% (4)	21.1% (4)	52.6% (10)	100% (19)
Computer Skills	0% (0)	5.9% (1)	17.6% (3)	23.5% (4)	5.9% (1)	47.1% (8)	100% (17)

The clustering-based hybrid approach employed in this study, which utilizes a hierarchical clustering method, yields three clusters that group courses exhibiting relatively similar structures in the distribution of grades according to the A–B and E–F parameters. Accordingly, it may be assumed that these courses share certain common characteristics, which may be related to course content features, teaching–learning methodologies, assessment systems, the responsible instructor, or other specific instructional components.

At the same time, it is important to note that although cluster formation is based on overall profile similarity rather than on a hierarchy of grade levels, the clustering results may nevertheless reveal certain dominant trends in grade distributions within specific clusters. These trends provide additional interpretative opportunities but do not constitute criteria for cluster definition. In the specific case examined in this study, it may be assumed that the clusters identified through clustering differ from one another in terms of structural tendencies in grade distributions. Specifically, the first cluster is characterized by a relatively substantial proportion of high grades (A–B) with a non-dominant distribution of low grades (E–F); the second cluster is marked by a concentration of intermediate grades (C–D), with high and low grades present at moderate levels; and the third cluster exhibits a relatively high concentration of low grades (E–F) accompanied by minimal representation of high grades.

Conclusion

This study examined the practical applicability of assessment-based, hybrid analytical approaches for course-level quality assurance in higher education using aggregated grade distribution data. Rather than focusing on individual students or instructors, the analysis was deliberately framed at the course level, reflecting the realities of institutional quality assurance processes where aggregated outcomes often constitute the primary available evidence. The findings demonstrate that outcome-level grade distribution data, when interpreted through structured and explainable analytical frameworks, can provide meaningful and actionable insights for data-informed decision making in quality assurance.

The empirical application of the time-based hybrid analytical approach highlighted its particular strength in identifying stable and recurring patterns in course outcomes across multiple academic years. By combining descriptive analysis, threshold-based indicators, and longitudinal trend analysis, this approach enables the detection of structural and time-consistent issues that are unlikely to be revealed through single-semester analysis. The results show that only a limited number of courses met the criteria for longitudinal examination, yet among these, recurring low-outcome signals were clearly identifiable. This finding underscores both the analytical robustness and the inherent limitation of time-based approaches: while they provide high-confidence signals regarding long-term course performance, their applicability is constrained by data availability and course continuity over time.

In contrast, the clustering-based hybrid analytical approach proved effective in contexts where longitudinal data are unavailable or where rapid, comparative interpretation of course outcomes is required. By treating courses as multidimensional objects defined by aggregated outcome characteristics and applying explainable unsupervised clustering techniques, this approach enables the identification of structural similarities and differences among courses within a single academic period. The resulting clusters do not represent predefined quality categories but rather provide a relative analytical space within which course-level performance profiles can be interpreted. This makes the clustering-based approach particularly suitable for exploratory analysis and operational quality assurance tasks, complementing the more stable but less inclusive time-based analysis.

Taken together, the empirical findings demonstrate that the value of hybrid analytical approaches lies not in their direct comparison as competing methods, but in their complementary roles within quality assurance processes. The time-based approach supports strategic, long-term evaluation by emphasizing stability and recurrence, while the clustering-based approach enhances sensitivity and inclusiveness by enabling the analysis of a broader set of courses within a single-semester framework. When used jointly, these approaches provide a more comprehensive and context-aware understanding of course-level outcomes than either method could achieve in isolation.

Several limitations of the study should be acknowledged. The analysis is based on aggregated assessment data from a single institutional context, which restricts the generalizability of the findings. Threshold values and outcome aggregations were applied as heuristic signals rather than normative benchmarks and therefore require careful contextual interpretation. In addition, clustering results depend on the chosen analytical representation and distance measures and should be interpreted as exploratory rather than deterministic indicators of course quality.

Despite these limitations, the study demonstrates that explainable, hybrid analytical frameworks can significantly enhance the interpretability and practical usability of assessment data in course-level quality assurance. Future research may extend this work by applying the proposed approaches across multiple institutions and academic programs, integrating additional outcome indicators, and embedding such analytical pipelines within institutional quality assurance cycles and digital dashboards. Rather than replacing pedagogical judgment, the approaches discussed in this study offer structured analytical support for reflective, evidence-informed quality improvement in higher education.

REFERENCES

Biggs, J., Tang, C., & Kennedy, G. (2022). Teaching for quality learning at university (5th ed.). McGraw-Hill Education.

Boretz, E. (2004). Grade inflation and the myth of student consumerism. *College Teaching, 52*(2), 42–46. https://doi.org/10.3200/CTCH.52.2.42-46

European Association for Quality Assurance in Higher Education. (2015). *Standards and guidelines for quality assurance in the European Higher Education Area (ESG).* https://ehea.info/media.ehea.info/file/ESG/00/2/ESG_2015_616002.pdf

Harvey, L., & Green, D. (1993). Defining quality. *Assessment & Evaluation in Higher Education, 18*(1), 9–34. https://doi.org/10.1080/0260293930180102

Martin, F., Dennen, V. P., & Bonk, C. J. (2020). A synthesis of systematic review research on emerging learning environments and technologies. *Educational Technology Research and Development, 68*(4), 1613–1633. https://doi.org/10.1007/s11423-020-09812-2

Rexwinkel, T., Haenen, J., & Pilot, A. (2013). Quality assurance in higher education: Analysis of grades for reviewing course levels. *Quality & Quantity, 47*(1), 581–598. https://doi.org/10.1007/s11135-011-9551-9

Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education, 26*(3), 482–496. https://doi.org/10.1016/j.tate.2009.06.007

Shafiq, D. A., Marjani, M., Habeeb, R. A. A., & Asirvatham, D. (2022). Student retention using educational data mining and predictive analytics: A systematic literature review. *IEEE Access, 10*, 72480–72503. https://doi.org/10.1109/ACCESS.2022.3188767

Tabatadze, B. (2023). Modern possibilities of data visualization in digital platform of Moodle learning management system. *Globalization and Business, 8*(16), 111–117. https://doi.org/10.35945/gb.2023.16.010

Tabatadze, B., & Sokhadze, E. (2023). Possibility of improving the training courses content based on statistical analysis of the collected points. *Globalization and Business, 8*(15), 54–56. https://doi.org/10.35945/gb.2023.15.005

Webber, K. L., & Zheng, H. (2020). Data analytics and the imperatives for data-informed decision making in higher education. In K. L. Webber & H. Zheng (Eds.), *Big data on campus: Data analytics and decision making in higher education* (pp. 3–29). Johns Hopkins University Press.