

A Data-Driven Analytics Configuration for Instructional Performance Monitoring in Digital Learning Ecosystems [†]

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Abstract

The increasing adoption of digital learning environments has generated large volumes of learner-generated data that can be leveraged to support instructional quality monitoring, educational performance assessment, and evidence-based decision-making. As educational institutions seek scalable mechanisms for evaluating teaching effectiveness within technology-enabled learning ecosystems, there is a growing need for analytics-driven systems capable of transforming learner feedback into actionable performance intelligence. This study proposes an Instructional Quality Analytics System (IQAS) designed to collect, process, analyze, and visualize instructional effectiveness indicators within digital learning environments. The proposed system architecture consists of four integrated components: feedback acquisition, instructional quality analytics, performance monitoring, and decision-support reporting. The framework utilizes structured learner-generated evaluation data to model instructional effectiveness across multiple dimensions, including content quality, instructional delivery, learning environment support, and instructional management practices. Through quantitative analytics mechanisms, the system generates performance indicators, identifies instructional strengths and improvement opportunities, and supports continuous quality assurance processes. To demonstrate the feasibility of the proposed architecture, a pilot implementation was conducted using evaluation data collected from higher education learners within a technology-supported educational environment. Analytical results indicated consistently positive instructional performance across all assessment dimensions, with content-related indicators exhibiting the strongest performance characteristics. The evaluation further demonstrated stable instructional quality profiles across learner groups, suggesting the suitability of the framework for institution-wide monitoring and benchmarking applications. The proposed Instructional Quality Analytics System contributes a scalable architecture for educational performance monitoring and instructional effectiveness assessment within digital learning ecosystems. By integrating feedback analytics, performance intelligence generation, and decision-support capabilities, the framework provides a foundation for next-generation educational monitoring platforms, quality assurance systems, and intelligent learning analytics environments. The study offers practical implications for the development of data-driven educational governance mechanisms that support continuous improvement, resource optimization, and evidence-based instructional decision-making.



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1. Introduction

The increasing adoption of digital learning ecosystems has transformed instructional performance monitoring into a data-driven and system-level concern. In technology-supported higher education, instruction is no longer evaluated only through conventional classroom observation or end-of-term appraisal. It can also be examined through structured learner-generated data, digital feedback records, platform-supported interactions, and institutional performance indicators. Learning analytics refers to the measurement, collection, analysis, and reporting of data about learners and their contexts for understanding and optimizing learning and the environments in which learning occurs [1]. Educational data mining applies computational and statistical methods to identify patterns in educational datasets that may support prediction, intervention, and improvement in teaching and learning systems [2]. These fields provide a strong basis for designing analytics configurations that convert learner feedback into actionable instructional performance intelligence. Within digital learning environments, instructional effectiveness may be understood as a multidimensional construct involving content quality, instructional delivery, learning environment support, and instructional management practices. These dimensions are important because effective instruction depends not only on teacher delivery but also on the organization of learning materials, clarity of learning tasks, accessibility of resources, responsiveness of feedback, and reliability of instructional support mechanisms. From an information systems perspective, system quality, information quality, service quality, user satisfaction, use, and net benefits are key dimensions for evaluating the success of technology-supported systems [3]. This perspective is relevant to digital learning ecosystems because instructional quality is shaped by how well educational content, digital platforms, feedback mechanisms, and support processes function as an integrated instructional system. Recent studies in learning analytics show that learner data can support evidence-based decision-making in higher education, particularly in identifying learning patterns, improving learning design, supporting student success, and informing institutional intervention strategies [4]. Learning dashboards and reporting systems have also been examined as tools for presenting analytics information in ways that support stakeholder interpretation and decision-making [5]. These developments indicate that educational data are not useful only for describing learner outcomes; they can also be configured into monitoring systems that identify instructional strengths, performance gaps, and areas for continuous improvement. UNESCO's 2023 Global Education Monitoring Report further emphasizes that digital technology should complement teaching and learning and that data and learning analytics can help guide and personalize learning experiences when used appropriately [6]. Despite these developments, much of the existing literature on learning analytics and educational data mining focuses on learning management systems, student performance prediction, engagement analytics, early warning systems, and learner-facing dashboards. Fewer studies examine how structured learner-generated evaluation data can be configured specifically for instructional performance monitoring in localized digital learning ecosystems. This gap is important because institutions need practical analytics models that can transform routine evaluation data into systematic evidence for instructional quality assurance, faculty development, curriculum review, and academic decision-making. In technical-vocational teacher education, this concern is especially significant because learners are prepared not only to acquire technical and professional competencies but also to develop future instructional

practice. Therefore, instructional performance monitoring must capture both the quality of teaching processes and the capacity of the digital learning environment to support organized, accessible, and responsive instruction. To address this gap, this study aims to design and pilot-test a data-driven analytics configuration for instructional performance monitoring in digital learning ecosystems. The proposed Instructional Quality Analytics System (IQAS) provides a structured system model composed of four integrated components: feedback acquisition, instructional quality analytics, performance monitoring, and decision-support reporting. The system uses learner-generated evaluation data to assess instructional performance across four dimensions: content quality, instructional delivery, learning environment support, and instructional management practices. Its main contribution lies in converting routine student evaluation data into organized performance indicators that can support evidence-based instructional decision-making, internal quality assurance, faculty development planning, digital resource management, and continuous improvement in technology-supported higher education. As an empirical validation and pilot demonstration, the proposed configuration was applied using evaluation data from Bachelor of Technical–Vocational Teacher Education (BTVTEd) learners at Caraga State University Cabadbaran Campus. The pilot analysis examined the level of instructional performance across the identified dimensions and tested whether learner evaluations differed significantly when grouped according to specialization. Through this pilot implementation, the study demonstrates how learner feedback can be configured as analytics input for scalable instructional performance monitoring in localized digital learning ecosystems.

2. Methodology

2.1. Research Design

This study employed a quantitative descriptive–comparative design to demonstrate a data-driven analytics configuration for instructional performance monitoring in a digital learning ecosystem. Descriptive analysis was used to summarize learner profiles and instructional performance ratings, while comparative analysis determined whether evaluations differed significantly by specialization. Learner responses were treated as structured evaluation data for generating instructional performance indicators across four dimensions: content quality, instructional delivery, learning environment support, and instructional management practices.

2.2. Participants and Sampling Procedure

The participants were 170 students officially enrolled in the Bachelor of Technical–Vocational Teacher Education (BTVTEd) program at Caraga State University Cabadbaran Campus during the period of data collection. They represented different year levels and specializations. Stratified random sampling was used to ensure year-level representation. The population was grouped into first-, second-, third-, and fourth-year strata, after which participants were randomly selected from each group. Specialization groups were used as the basis for comparative analysis.

2.3. Research Instrument

A structured survey questionnaire adapted from instruments on teaching quality and quality assurance in technical–vocational education [7] was used. It consisted of three parts: demographic and academic profile, Likert-scale items on instructional performance, and an open-ended item for suggestions. The quantitative items were organized into four dimensions: content quality, instructional delivery, learning environment support, and instructional management practices. These dimensions served as the main indicators of the proposed Instructional Quality Analytics System.

2.4. Data Gathering Procedure

Formal permission was secured from the Dean of the College of Industrial Technology and Teacher Education. After approval, the researcher coordinated with concerned faculty members and program personnel for survey administration. Participants were informed about the study's purpose, voluntary participation, confidentiality of responses, and their right to withdraw. Completed questionnaires were checked for completeness, encoded, and organized according to the instructional performance dimensions and learner specialization.

2.5. Instructional Quality Analytics Configuration

The proposed Instructional Quality Analytics System consisted of four stages: feedback acquisition, instructional quality analytics, performance monitoring, and decision-support reporting. In the feedback acquisition stage, structured learner evaluation data were collected through the survey. In the analytics stage, valid responses were encoded, grouped, and statistically processed. In the performance monitoring stage, descriptive and comparative results were used to assess instructional performance across the four dimensions. In the decision-support reporting stage, the results were interpreted to identify instructional strengths, improvement areas, and patterns across specialization groups.

2.6. Ethical Considerations

The study observed voluntary participation, informed consent, confidentiality, and responsible handling of learner-generated data. No personally identifiable information was disclosed, and results are reported only in aggregate form. The data were used solely for academic research, instructional improvement, and quality assurance purposes.

2.7. Data Analysis

Frequency and percentage were used to describe the participants' profile. Mean and standard deviation were used to determine the level of instructional performance across the four dimensions. One-way analysis of variance was used to test whether evaluations differed significantly by specialization, with all tests interpreted at the 0.05 level of significance. No comparative tests were conducted for age, sex, or year level because specialization was the main grouping variable. The four-point Likert scale was interpreted as follows: 1.00–1.50 = Very Low Level; 1.51–2.50 = Low Level; 2.51–3.50 = High Level; and 3.51–4.00 = Very High Level. The dataset was checked for completeness before analysis. However, normality and homogeneity of variance tests were not extensively reported, and the unequal distribution of participants across specialization groups may have limited the sensitivity of the comparative analysis.

2.8. Validity and Reliability of the Instrument

The questionnaire was reviewed by faculty experts for clarity, relevance, appropriateness, and alignment with the study objectives. It was pilot-tested with 35 comparable participants who were excluded from the final sample. Reliability analysis yielded a Cronbach's alpha coefficient of 0.941, indicating excellent internal consistency and confirming the instrument's suitability for generating instructional performance data.

3. Results and Discussion

The findings are presented according to the major components of the proposed Instructional Quality Analytics System (IQAS): learner profile, content quality, instructional delivery, learning environment support, instructional management, and specialization-based comparison. Since IQAS is proposed rather than fully deployed as an operational

platform, the results are interpreted as baseline learner-evaluation outputs generated through conventional survey tabulation and statistical analysis. The discussion therefore explains both the observed instructional quality patterns and how these data could be transformed into structured analytics indicators for monitoring, visualization, and decision-support reporting.

3.1. Profile of Learner-Generated Evaluation Dataset for Instructional Performance Analytics

Table 1 presents the learner-generated evaluation dataset used for instructional performance analytics. The dataset consisted of 170 BTVTEd students, most of whom were 19–21 years old ($f = 101$, 59.41%), followed by those aged 22–24 years old ($f = 33$, 19.41%). This indicates that the responses were largely drawn from traditional college-age learners. Female students represented the majority of respondents ($f = 108$, 63.53%), while male students accounted for 35.29% ($f = 60$).

Table 1. Profile of learner-generated evaluation dataset for instructional performance analytics.

Category	Subcategory	Frequency	Percentage (%)
Age Group	18 years old and below	22	12.94
	19–21 years old	101	59.41
	22–24 years old	33	19.41
	25 years old and above	14	8.24
Sex	Male	60	35.29
	Female	108	63.53
	Prefer not to say	2	1.18
Specialization	Automotive Technology	20	11.76
	Architectural Drafting Technology	15	8.82
	Civil and Construction Technology	3	1.76
	Electrical Technology	5	2.94
	Electronics Technology	27	15.88
	Food Service Management	49	28.82
	Garments, Fashion, and Design	44	25.88
	Welding Fabrication Technology	7	4.12
Year Level	First Year	81	47.65
	Second Year	42	24.71
	Third Year	26	15.29
	Fourth Year	21	12.35

In terms of specialization, Food Service Management had the highest representation ($f = 49$, 28.82%), followed by Garments, Fashion, and Design ($f = 44$, 25.88%) and Electronics Technology ($f = 27$, 15.88%). Smaller groups were observed in Civil and Construction Technology ($f = 3$, 1.76%), Electrical Technology ($f = 5$, 2.94%), and Welding Fabrication Technology ($f = 7$, 4.12%). This uneven distribution should be considered when interpreting specialization-based comparisons, as small subgroup sizes may reduce the sensitivity of statistical analysis. The year-level distribution also shows that first-year students formed the largest group ($f = 81$, 47.65%), followed by second-year students ($f = 42$, 24.71%), third-year students ($f = 26$, 15.29%), and fourth-year students ($f = 21$, 12.35%). Since the dataset is more heavily represented by lower-year learners, the results may reflect the evaluation perspectives of students with relatively shorter exposure to the program and its digital learning practices. Thus, the profile defines the scope and structure of the dataset used in the proposed IQAS. In learning analytics, learner-generated data are used to measure, analyze, and report learning contexts for improving educational environments [1]. However, educational datasets must be interpreted in relation to their representativeness, subgroup distribution, and institutional context [2,4]. Thus, while the dataset supports the

feasibility of using structured learner feedback for instructional performance monitoring, subgroup imbalance should be acknowledged as a limitation in comparative interpretation.

3.2. Content Quality Indicators for Instructional Performance Analytics

Table 2 shows that the content quality dimension obtained an overall mean of 3.35 (SD = 0.32), interpreted as 'High'. This indicates that students generally perceived the course content as structured, relevant, current, and supportive of instructional performance in the digital learning ecosystem. The relatively low standard deviation suggests consistency in learner ratings across the content indicators.

Table 2. Content quality indicators for instructional performance analytics.

Content Quality Indicator	Mean	SD	Rank	Performance Level
1. Lessons follow a structured and logical sequence.	3.25	0.45	10	High
2. Course content is relevant to industry needs.	3.32	0.48	7	High
3. Teachers integrate real-world applications into lessons.	3.36	0.49	5	High
4. Learning materials are up-to-date.	3.34	0.55	6	High
5. The course encourages critical thinking and problem-solving.	3.42	0.51	1.5	High
6. The course includes theoretical and practical knowledge necessary for industry readiness.	3.42	0.49	1.5	High
7. Expectations about course content were met.	3.30	0.56	8	High
8. Knowledge gained from the course aligns with career goals.	3.38	0.51	3.5	High
9. Content delivery promotes deep understanding.	3.38	0.56	3.5	High
10. Course content reflects current trends and developments in the field.	3.31	0.51	9	High
Overall Content Quality	3.35	0.32		High

Note: Scale interpretation: 1.00–1.50 = Very Low; 1.51–2.50 = Low; 2.51–3.50 = High; 3.51–4.00 = Very High.

The highest-rated indicators were the encouragement of critical thinking and problem-solving ($M = 3.42$, $SD = 0.51$) and the inclusion of theoretical and practical knowledge necessary for industry readiness ($M = 3.42$, $SD = 0.49$). These findings indicate that students perceived the course content as supportive of higher-order thinking and applied learning. In technical–vocational teacher education, this is important because instructional content must connect conceptual understanding with practical and industry-oriented competence. The results are consistent with constructive alignment, which emphasizes coherence among learning outcomes, learning activities, and assessment tasks [8]. Career-goal alignment and content delivery that promotes deep understanding both obtained a mean of 3.38. These results suggest that students recognized the relevance and clarity of the instructional content. However, the lowest-rated indicator was the logical sequencing of lessons ($M = 3.25$, $SD = 0.45$), followed by content responsiveness to current trends and developments in the field ($M = 3.31$) and relevance to industry needs ($M = 3.32$). Although all indicators remained at a high level, these relatively lower scores suggest that instructional content may be strengthened through clearer sequencing, periodic updating, and closer alignment with changing industry practices. From an IQAS perspective, Table 2 demonstrates how routine learner feedback can be converted into content quality indicators. Instead of treating the results only as end-of-term survey summaries, the proposed system could organize them

into a reusable monitoring layer for tracking course relevance, content structure, industry alignment, and instructional clarity across courses, specializations, and academic periods.

3.3. Instructional Delivery Indicators for Instructional Performance Analytics

Table 3 presents the instructional delivery indicators generated from structured learner evaluation data. The overall mean of 3.30 (SD = 0.24), interpreted as High, indicates that students generally evaluated instructional delivery positively. The low standard deviation suggests that learner ratings were relatively consistent across the delivery indicators.

Table 3. Instructional delivery indicators for instructional performance analytics.

Instructional Delivery Indicator		Mean	SD	Rank	Performance Level
1.	The teacher uses varied methods to accommodate different topics and learners.	3.27	0.52	8	High
2.	Lessons promote active participation and student engagement.	3.24	0.44	9	High
3.	Teaching strategies are adapted to different learning styles.	3.23	0.42	10	High
4.	Teachers provide timely and helpful feedback on student performance.	3.30	0.46	6	High
5.	Teaching approaches develop practical and industry-relevant skills.	3.35	0.48	1.5	High
6.	Technology is integrated effectively to support learning.	3.29	0.46	7	High
7.	Students are satisfied with how lessons are delivered.	3.33	0.47	4	High
8.	Teaching methods help students understand and apply what they learn.	3.34	0.48	3	High
9.	Teachers regularly evaluate and improve their teaching strategies.	3.32	0.48	5	High
10.	Teachers facilitate collaborative activities to support peer learning.	3.35	0.50	1.5	High
Overall Instructional Delivery		3.30	0.24		High

Note: Scale interpretation: 1.00–1.50 = Very Low; 1.51–2.50 = Low; 2.51–3.50 = High; 3.51–4.00 = Very High.

The highest-rated indicators were the development of practical and industry-relevant skills ($M = 3.35$, $SD = 0.48$) and the facilitation of collaborative activities for peer learning ($M = 3.35$, $SD = 0.50$). These results suggest that instructional delivery was strongest in applied learning and collaborative engagement. This is significant in technical–vocational teacher education because effective instruction should connect teaching strategies with practical competence, peer interaction, and workplace-relevant tasks. Teaching methods that helped students understand and apply what they learned also received a high rating ($M = 3.34$, $SD = 0.48$), followed by student satisfaction with lesson delivery ($M = 3.33$, $SD = 0.47$) and regular improvement of teaching strategies ($M = 3.32$, $SD = 0.48$). These findings indicate that students viewed the delivery process as generally understandable, applicable, and responsive. The lowest-rated indicators were the adaptation of teaching strategies to different learning styles ($M = 3.23$, $SD = 0.42$), promotion of active participation and engagement ($M = 3.24$, $SD = 0.44$), and use of varied methods to accommodate different topics and learners ($M = 3.27$, $SD = 0.52$). Although these indicators remained at a high level, they point to areas for improvement in instructional differentiation, engagement design, and method variation. For the proposed IQAS, these results may serve as instructional

delivery indicators that can be monitored across instructors, subjects, and learner groups. By organizing delivery-related feedback into analytics categories, the system could help identify whether applied learning, collaborative learning, technology integration, and differentiated instruction are consistently supported across the program.

3.4. Learning Environment Support Indicators for Instructional Performance Analytics

Table 4 presents the learning environment support indicators derived from structured learner evaluation data. The overall mean of 3.26 (SD = 0.31), interpreted as High, indicates that students generally evaluated the learning environment as supportive of instructional performance.

Table 4. Learning environment support indicators for instructional performance analytics.

Learning Environment Support Indicator	Mean	SD	Rank	Performance Level
1. The classroom/laboratory is well-equipped for practical training.	3.22	0.55	8	High
2. The school provides enough learning resources, tools, and equipment.	3.19	0.50	9.5	High
3. The learning environment supports both individual and group work.	3.31	0.46	3	High
4. Teachers encourage a respectful and inclusive classroom atmosphere.	3.34	0.47	1	High
5. The school provides academic support for struggling students.	3.26	0.48	5.5	High
6. Students can access industry partnerships or internships for training.	3.26	0.56	5.5	High
7. The teaching environment meets expectations for technical–vocational training.	3.33	0.53	2	High
8. Students feel supported with adequate tools and facilities during classes.	3.25	0.56	7	High
9. There is a safe and comfortable learning space for all students.	3.24	0.47	6	High
10. The scheduling of classes and laboratory sessions is convenient and manageable.	3.19	0.52	9.5	High
Overall Learning Environment Support	3.26	0.31		High

Note: Scale interpretation: 1.00–1.50 = Very Low; 1.51–2.50 = Low; 2.51–3.50 = High; 3.51–4.00 = Very High.

The highest-rated indicator was the presence of a respectful and inclusive classroom atmosphere ($M = 3.34$, $SD = 0.47$), followed by the teaching environment meeting expectations for technical–vocational training ($M = 3.33$, $SD = 0.53$) and support for both individual and group work ($M = 3.31$, $SD = 0.46$). These findings indicate that the strongest learning-condition areas were classroom climate, suitability of the training environment, and support for varied learning arrangements. This result is important because learning environments in digital and technology-supported education should not only provide access to tools but also create conditions that support participation, inclusion, and meaningful engagement. UNESCO emphasizes that digital technology in education should address quality, equity, inclusion, and system management rather than focus on technology adoption alone [6]. The lower-ranked indicators were the provision of sufficient learning resources, tools, and

equipment ($M = 3.19$, $SD = 0.50$) and the convenience of class and laboratory scheduling ($M = 3.19$, $SD = 0.52$). The classroom or laboratory being well-equipped for practical training also ranked relatively low ($M = 3.22$, $SD = 0.55$). Although still rated High, these indicators suggest areas where institutional support may be strengthened, particularly in resource adequacy, laboratory readiness, and scheduling coordination. Within IQAS, learning environment support indicators could help administrators identify recurring concerns related to facilities, equipment, laboratory access, scheduling, and academic support. These indicators are especially relevant in technical–vocational programs where practical training depends heavily on adequate tools, safe learning spaces, and organized laboratory use.

3.5. Instructional Management Indicator for Instructional Performance Analytics

Table 5 presents the instructional management indicators derived from structured learner evaluation data. The overall mean of 3.28 ($SD = 0.27$), interpreted as High, indicates that students generally evaluated instructional management practices positively.

Table 5. Instructional management indicators for instructional performance analytics.

Instructional Management Indicator		Mean	SD	Rank	Performance Level
1.	The teacher starts and ends class on time.	3.09	0.48	10	High
2.	The teacher maintains professionalism in the classroom.	3.35	0.50	2	High
3.	The course syllabus and expectations are clearly communicated.	3.31	0.51	5	High
4.	The grading and assessment system is fair and transparent.	3.32	0.47	4	High
5.	Teachers provide opportunities for consultation and mentoring.	3.22	0.44	8	High
6.	Teachers encourage student feedback and use it to improve course delivery.	3.34	0.50	3	High
7.	The way classes are managed meets student expectations.	3.12	0.41	9	High
8.	Students are satisfied with the fairness and clarity of course administration.	3.26	0.46	7	High
9.	The teacher manages classroom behavior effectively.	3.30	0.47	6	High
10.	Class schedules and deadlines are well organized and reasonable.	3.45	0.51	1	High
Overall Instructional Management		3.28	0.27		High

Note: Scale interpretation: 1.00–1.50 = Very Low; 1.51–2.50 = Low; 2.51–3.50 = High; 3.51–4.00 = Very High.

The highest-rated indicator was the organization and reasonableness of class schedules and deadlines ($M = 3.45$, $SD = 0.51$), followed by teacher professionalism in the classroom ($M = 3.35$, $SD = 0.50$) and the use of student feedback to improve course delivery ($M = 3.34$, $SD = 0.50$). These results suggest that the strongest management-related areas were scheduling, professional conduct, and feedback-informed improvement. From a constructive alignment perspective, clear organization and feedback processes are important because teaching activities, assessment expectations, and learning support must be coherently linked to intended learning outcomes [8]. The lower-ranked indicators were starting and ending class on time ($M = 3.09$, $SD = 0.48$), class management meeting student expectations ($M = 3.12$, $SD = 0.41$), and opportunities for consultation and mentoring ($M = 3.22$, $SD = 0.44$). Although these indicators remained at a high level, they suggest improvement

areas in time management, class administration, and learner support. In a digital learning ecosystem, these indicators are important because instructional management affects the predictability, accessibility, and responsiveness of the learning process. For the proposed IQAS, instructional management data could be converted into performance indicators for monitoring course administration, feedback use, mentoring opportunities, schedule organization, and classroom management. This would allow program heads and quality assurance personnel to identify management-related concerns more systematically and compare patterns across courses or academic terms.

3.6. Comparative Analysis of Instructional Performance Indicators by Learner Specialization

Table 6 presents the comparative analysis of instructional performance indicators when learner ratings were grouped according to specialization. Using one-way ANOVA at $\alpha = 0.05$, all instructional performance dimensions obtained p -values greater than 0.05: content quality ($F = 1.68, p = 0.12$), instructional methods ($F = 1.06, p = 0.39$), instructional delivery ($F = 1.60, p = 0.14$), learning environment support ($F = 0.37, p = 0.92$), and instructional management ($F = 1.18, p = 0.32$). Therefore, the null hypothesis was not rejected across all dimensions.

Table 6. Comparative analysis of instructional performance indicators by learner specialization.

Instructional Performance Dimension		F-Value	p -Value	Statistical Decision	Interpretation
1.	Content Quality	1.68	0.12	Do not reject H_0	Not significant
2.	Instructional Methods	1.06	0.39	Do not reject H_0	Not significant
3.	Instructional Delivery	1.60	0.14	Do not reject H_0	Not significant
4.	Learning Environment Support	0.37	0.92	Do not reject H_0	Not significant
5.	Instructional Management	1.18	0.32	Do not reject H_0	Not significant

Note: Analysis used one-way ANOVA at $\alpha = 0.05$. H_0 = no significant difference in instructional performance ratings across learner specialization groups.

These results indicate that learner ratings did not differ significantly across specialization groups. In practical terms, students from different technical–vocational specializations evaluated instructional performance in a generally similar manner. This suggests a stable instructional quality profile across the learner groups included in the dataset. However, this result should not be interpreted as proof that all specializations experience identical instructional conditions. The unequal number of respondents across specializations and the limited subgroup sizes may have reduced the sensitivity of the ANOVA results, particularly for smaller groups such as Civil and Construction Technology, Electrical Technology, and Welding Fabrication Technology. Therefore, the non-significant results should be interpreted as evidence of no detected statistical difference within the current dataset, rather than as definitive evidence of uniform instructional experience. If implemented, IQAS could strengthen comparative analysis by automatically grouping learner responses by specialization, computing performance indicators, visualizing group-level patterns, and tracking changes across academic periods. This would extend conventional ANOVA output into a more dynamic benchmarking process for instructional quality monitoring.

3.7. Synthesis of Instructional Performance Analytics Findings

Across Tables 2–5, all instructional performance dimensions were rated High: content quality ($M = 3.35$), instructional delivery ($M = 3.30$), instructional management ($M = 3.28$), and learning environment support ($M = 3.26$). These results suggest that students gener-

ally perceived the instructional system as effective, supportive, and relevant to technical-vocational teacher education. The strongest areas were related to critical thinking, applied knowledge, collaborative learning, schedule organization, professional conduct, and inclusive classroom climate. At the same time, the relatively lower-rated indicators point to specific improvement areas, including lesson sequencing, responsiveness to current industry trends, instructional differentiation, active engagement, resource adequacy, laboratory readiness, scheduling coordination, punctuality, and mentoring opportunities. These areas do not indicate weak performance since all remained at a high level, but they provide practical directions for instructional enhancement. The comparative analysis further showed no statistically significant differences across learner specialization groups. This suggests that the observed instructional performance ratings were generally consistent across the sampled specializations. However, subgroup imbalance limits the strength of this interpretation and should be addressed in future implementation through larger and more proportionate samples. From a systems perspective, the findings demonstrate the usefulness of learner-generated evaluation data as input for instructional quality analytics. Learning analytics emphasizes the measurement, collection, analysis, and reporting of learner and contextual data to improve educational environments [1], while educational data mining supports the identification of patterns from educational datasets that may guide instructional and institutional improvement [2]. Dashboard-based reporting can further improve the usefulness of evaluation data by helping stakeholders interpret indicators and support evidence-based decision-making [5]. Thus, the proposed IQAS could improve the management of instructional evaluation data by transforming routine survey responses into structured performance indicators. Through data validation, indicator grouping, scoring, visualization, and reporting, the system could support more seamless monitoring of content quality, delivery practices, learning environment support, instructional management, and specialization-based trends. In this way, the study provides a data-driven basis for improving instructional quality assurance in digital learning ecosystems.

4. Conclusions

This study proposed an Instructional Quality Analytics System (IQAS) for converting learner-generated evaluation data into structured indicators for instructional performance monitoring. Based on responses from 170 BTVTED students, the findings showed high ratings across content quality, instructional delivery, learning environment support, and instructional management. The strongest areas were critical thinking, applied knowledge, collaborative learning, schedule organization, professionalism, and inclusive classroom climate. However, areas such as lesson sequencing, industry responsiveness, instructional differentiation, resource adequacy, laboratory readiness, punctuality, and mentoring still require improvement. The ANOVA results showed no significant differences in instructional performance ratings across learner specializations, suggesting generally consistent evaluations among the sampled groups. However, this finding should be interpreted cautiously due to unequal subgroup sizes. Overall, the study demonstrates that learner evaluation data can serve as a useful input for instructional quality analytics. If implemented, IQAS could support indicator grouping, visualization, trend monitoring, and decision-support reporting for program heads, instructors, and quality assurance personnel. The study is limited by its single-program context, uneven specialization distribution, and reliance on learner perception data. Future research may implement IQAS as a functional platform, use larger and more balanced samples, integrate instructor and administrative data, and examine its effectiveness in supporting continuous instructional quality improvement.

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Abbreviations

The following abbreviations are used in this manuscript:

IQAS	Instructional Quality Analytics System
BTVTed	Bachelor of Technical–Vocational Teacher Education
UNESCO	United Nations Educational, Scientific and Cultural Organization

References

1. Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review. Available online: <https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education> (accessed on 29 June 2026).
2. Romero, C.; Ventura, S. Educational Data Mining and Learning Analytics: An Updated Survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2020**, *10*, e1355. [CrossRef]
3. Delone, W.H.; McLean, E.R. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *J. Manag. Inf. Syst.* **2003**, *19*, 9–30. [CrossRef]
4. Ifenthaler, D.; Yau, J.Y.-K. Utilising Learning Analytics to Support Study Success in Higher Education: A Systematic Review. *Educ. Technol. Res. Dev.* **2020**, *68*, 1961–1990. [CrossRef]
5. Schwendimann, B.A.; Rodríguez-Triana, M.J.; Vozniuk, A.; Prieto, L.P.; Boroujeni, M.S.; Holzer, A.; Gillet, D.; Dillenbourg, P. Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research. *IEEE Trans. Learn. Technol.* **2017**, *10*, 30–41. [CrossRef]
6. Global Education Monitoring Report Team. *Global Education Monitoring Report, 2023: Technology in Education: A Tool on Whose Terms?* UNESCO: Paris, France, 2023; Available online: <https://unesdoc.unesco.org/ark:/48223/pf0000385723> (accessed on 29 June 2026).
7. Wafudu, S.J.; Kamin, Y.B.; Marcel, D. Validity and reliability of a questionnaire developed to explore quality assurance components for teaching and learning in vocational and technical education. *Humanit. Soc. Sci. Commun.* **2022**, *9*, 303. [CrossRef]
8. Enhancing Teaching Through Constructive Alignment. *High. Educ.* **1996**, *32*, 347–364. [CrossRef]

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