TURNING NUMBERS INTO QUALITY: A LEARNING ANALYTICS-BASED ACADEMIC STAFF EVALUATION MODEL IN HIGHER EDUCATION

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ABSTRACT
The purpose of this study is to examine the longitudinal stability, structural coherence, and predictive capacity of a learning analytics-based academic staff evaluation model in higher education. Specifically, the study investigates the relationships between student feedback, composite academic staff rating scores, and demographic performance indicators within a digitally institutionalised quality assurance system.
This research adopts a quantitative, correlational, and longitudinal design. The dataset comprises institutional performance records for 565 faculty members, collected over seven years (2018–2024). Data were obtained from the digital academic staff rating system, online student feedback platform, learning management system analytics, and research and institutional service databases. Statistical analyses included descriptive statistics, longitudinal trend analysis, Pearson correlation, regression modelling, inter-year correlation heatmap analysis, and group-based comparisons across gender and age categories.
The findings reveal a consistent upward trend in academic staff performance over time, indicating continuous professional development under digital performance monitoring. A strong, positive, and statistically significant relationship was identified between student feedback scores and composite academic staff ratings, confirming that feedback is a key predictor of academic performance. Female faculty members demonstrate slightly higher average performance, whereas the 30–39 age group exhibits the strongest performance dynamics. Inter-year correlation results show that the evaluation system achieved high institutional stability and predictive reliability after 2021.

Keywords: *learning analytics, academic staff evaluation, digital quality assurance, student feedback, higher education*

Introduction

The rapid digital transformation of higher education has fundamentally reshaped institutional governance, teaching–learning processes, and quality assurance mechanisms. Universities are increasingly operating as data-driven organisations in which digital technologies and learning analytics support decision-making, performance monitoring, and academic development. In this context, academic staff evaluation has evolved from traditional episodic assessment practices to continuous, technology-supported, multi-criteria performance monitoring systems.

In the contemporary higher education landscape, academic staff performance is no longer evaluated solely on the basis of classroom observation or isolated research outputs. Instead, integrated digital evaluation models combine teaching quality, student feedback, research productivity, and institutional service within unified performance architectures. Learning analytics, online student evaluation systems, and institutional performance dashboards enable universities to monitor academic quality in real time and to implement evidence-based quality assurance strategies (Daniel, 2015; Siemens & Gasevic, 2012).

The academic relevance and timeliness of academic staff evaluation are directly connected to global developments in digital governance, accountability, and outcome-based education. International accreditation frameworks and quality standards increasingly require transparent, data-based performance monitoring of academic staff. As a result, digital academic staff evaluation systems have become central operational components of internal quality assurance infrastructures.

The current state of the literature demonstrates significant growth in studies focusing on digital assessment, student feedback, learning analytics, and data-driven decision-making in higher education (Spooren et al., 2013; Viberg et al., 2018). However, most existing studies examine these components separately and within short-term or cross-sectional research designs. There remains a limited number of large-scale longitudinal empirical studies that validate the long-term structural stability, predictive reliability, and developmental function of integrated academic staff evaluation systems.

Against this background, this study emerges from the institutional need to evaluate the effectiveness, stability, and predictive capacity of a learning analytics-based academic staff evaluation model implemented at a teacher education university. The motivation for this research is the need to move beyond descriptive digital monitoring toward empirically validated, development-oriented performance intelligence systems that support sustainable academic quality.

Aim

The main aim of this study is to examine the longitudinal stability, structural coherence, and predictive capacity of a learning analytics-based academic staff evaluation model in higher education. Specifically, the study aims to analyse the relationships between student feedback, composite academic staff rating scores, and demographic performance indicators (gender and age) within a digitally institutionalised quality assurance system. In addition, the study seeks to determine whether student feedback is a significant predictor of academic staff performance within a multi-criteria digital evaluation framework.

Significance

The significance of this study lies in its empirical contribution to educational technology, learning analytics, and higher education quality assurance. By providing a large-scale longitudinal validation of a digitally supported academic staff evaluation system, the study offers original evidence on how integrated performance monitoring models evolve into stable institutional governance mechanisms.

From a theoretical perspective, the study strengthens the conceptual link between learning analytics and academic staff evaluation by demonstrating that student feedback functions as a structural predictor of academic performance rather than merely as a perceptual indicator. From a practical perspective, the findings offer direct implications for the design of digital performance dashboards, professional development systems, and data-driven quality assurance frameworks. At the policy level, the study provides evidence-based guidance for institutions seeking to institutionalise transparent, predictive, and development-oriented digital evaluation systems.

Theoretical Framework

This study is grounded in three interrelated theoretical foundations: learning analytics theory, digital quality assurance models, and data-driven academic governance. Learning analytics provides the scientific framework for the measurement, analysis, and interpretation of educational data generated through digital environments (Siemens & Gasevic, 2012). It enables the transformation of raw instructional and feedback data into actionable performance intelligence.

Digital quality assurance theory emphasises the integration of continuous digital monitoring, performance indicators, and feedback loops into institutional improvement cycles. Within this framework, academic staff evaluation functions not as a static control mechanism but as a dynamic developmental mechanism that supports professional growth and pedagogical innovation.

Data-driven academic governance constitutes the third theoretical foundation of the study. It refers to the systematic use of empirical data for academic decision-making, strategic planning, and quality management (Daniel, 2015). Within this context, academic staff performance indicators, student feedback, and research productivity metrics are integrated into unified digital governance architectures that enable predictive and evidence-based institutional leadership.

Literature Review

Previous research has extensively examined student evaluations of teaching as one of the most widely used indicators of instructional quality in higher education. Meta-analytic studies confirm that student feedback is significantly associated with teaching effectiveness, course organisation, and learning climate (Spooren et al., 2013; Spooren et al., 2008). However, concerns regarding subjectivity and contextual bias remain central to ongoing academic debates.
Learning analytics research has demonstrated strong potential for supporting decision-making, performance prediction, and instructional improvement through real-time data analysis (Viberg et al., 2018; Ifenthaler & Yau,

2020). While most learning analytics studies remain student-centred, recent developments highlight the growing use of analytics to monitor academic staff performance.

Several major research strands have shaped the conceptual foundations of learning analytics. Gašević et al. (2015) emphasise that learning analytics should not be reduced to a set of technical indicators; rather, its core purpose is to generate deeper insights into learning processes themselves. From a broader perspective, Ferguson (2012) provides a systematic classification of the field's origins, developmental trajectories, and emerging challenges.

Meta-analytic examinations of citation networks further reveal how the field's intellectual structure has evolved, with Dawson et al. (2014) demonstrating the consolidation of learning analytics as a coherent research domain. In parallel, recent scholarship highlights the growing role of artificial intelligence in enhancing analytical models, with Tariq (2025) showing that AI-supported approaches can significantly improve the accuracy of predicting student performance. Furthermore, Ifenthaler et al. (2019) provide a comprehensive analysis of how learning analytics can be strategically leveraged to support student success across diverse educational contexts.

The practical applications of learning analytics rely heavily on LMS log data, student behavioural traces, and predictive modelling. The landmark "Course Signals" study conducted at Purdue University (Arnold & Pistilli, 2012) demonstrates that early-warning systems can substantially improve student success. Similarly, Macfadyen and Dawson (2010) show that LMS-generated behavioural indicators can be transformed into actionable insights to support real-time instructional decision-making.

Studies focused on predictive performance modelling provide additional evidence for the analytical power of learning analytics frameworks. Using LMS data, You (2016) identifies key behavioural indicators that reliably predict course achievement. Mythili and Shanavas (2014) complement this work by comparing the performance of multiple classification algorithms in predicting student outcomes. More recent analytics approaches—such as those proposed by Jiang et al. (2021)—demonstrate that fine-grained process data can be used to infer complex problem-solving strategies in large-scale assessments.

Beyond predictive analytics, research in digital learning design highlights how instructional structures shape learner engagement and academic outcomes. A large-scale cross-institutional study by Rienties and Toetenel (2016) shows that learning design is a strong determinant of student behaviour, satisfaction, and performance. Evidence from blended learning environments also confirms high levels of student satisfaction (Freij, 2022). Additionally, research on flipped classroom models demonstrates significant improvements in motivation and perceived learning quality (Sergis et al., 2017). In a complementary line of inquiry, Henderson et al. (2017) explore how students conceptualise "useful" digital technologies, revealing notable links between perceived usefulness and learning outcomes.

The effectiveness of learning analytics systems is also shaped by users' trust in algorithmic mechanisms. Kizilcec (2016) finds that the level of transparency embedded in algorithmic interfaces significantly influences trust and decision-making behaviours, highlighting the importance of ethical and psychological considerations in system design.

Finally, broader literature on student success provides essential context for understanding performance dynamics. A foundational review by Kuh et al. (2006) identifies the institutional, pedagogical, and behavioural conditions that most strongly influence student achievement. In parallel, Hallinger et al. (2014) show that systematic teacher evaluation plays a critical role in school improvement, reinforcing the importance of robust performance measurement systems in educational environments.

Data-driven decision-making in education has been shown to enhance institutional transparency, accountability, and strategic coherence (Schildkamp et al., 2013). However, existing studies predominantly rely on short-term datasets and fragmented performance indicators. The literature reveals a clear gap in longitudinal, institution-wide validation of integrated academic staff evaluation systems that combine learning analytics, student feedback, and digital quality assurance mechanisms within a unified framework.

Sharifov (2022) demonstrates that multi-dimensional staff rating and performance evaluation mechanisms exert a substantial influence on university faculty members' professional behaviour, research productivity, and pedagogical effectiveness. Complementing this perspective, Sharifov and Mammadzade (2022) argue that integrative institutional evaluation systems play an increasingly critical role in enhancing governance efficiency, strengthening accountability, and fostering a sustainable culture of quality in higher education.

By addressing this gap, the present study contributes a rare large-scale longitudinal empirical analysis of a learning analytics-based academic staff evaluation model. It advances the understanding of digital performance governance in higher education.

Methodology
This section describes the research procedures in detail and in a reproducible manner. The methodological framework, sample characteristics, data collection instruments, application process, and statistical analysis techniques are systematically presented.

This study adopted a quantitative, correlational, and longitudinal research design. Since the primary aim of the research was to statistically examine the relationships between student feedback, academic staff performance indicators, and demographic variables over time, a longitudinal design was selected. The study is grounded in the learning analytics and data-driven governance paradigms.

The research design includes:

- Longitudinal analysis of academic performance dynamics across the years 2018–2024,
- Examination of correlations between student satisfaction and academic rating scores,
- Analysis of the effects of age and gender variables on academic staff performance.

The study sample comprises 565 academic staff members, evaluated over seven years (2018–2024). The participants were classified according to the following characteristics:

- Gender: male and female,
- Age groups: <30, 30–39, 40–49, 50–59, 60+,
- Academic positions: lecturer, senior lecturer, associate professor, professor, department head, vice dean, and dean.

The sampling strategy was based on a complete institutional census, meaning that all active academic staff members within the specified period were included in the study rather than a selected subsample.
Data were obtained from four primary digital sources:

1. *Institutional academic rating system*. This system provided annual composite performance scores based on teaching, research, and social/service activities.
2. Online student feedback survey system. Student evaluations of teaching quality were collected via standardised digital surveys and reported as percentage-based satisfaction scores.
3. *Learning management system (LMS) analytics module.* Instructional engagement indicators such as online participation, assignment completion, and assessment records were extracted from LMS logs.
4. *Research and institutional activity database.* Data on scientific publications, research projects, conference participation, and administrative responsibilities were retrieved from internal institutional records.

The data collection process was conducted in the following stages:

- Official institutional permission was obtained prior to data access,
- All datasets were processed in a fully anonymised format,
- Student feedback data were analysed using coded instructor identifiers only,
- All procedures strictly complied with ethical research standards,
- Collected data were used exclusively for scientific research purposes.

Statistical analyses were conducted using SPSS. The following techniques were applied:

- Descriptive statistics: mean, median, standard deviation,
- Longitudinal trend analysis**:** performance dynamics from 2018 to 2024,
- Pearson correlation analysis: relationship between student feedback and academic rating scores,
- Regression modelling: predictive role of student feedback,
- Heatmap-based inter-year correlation analysis: institutional system stability,
- Distributional analysis: outlier detection and right-skewness evaluation.

All analytical results were visualised using histograms, scatter plots, box plots, and correlation heatmaps to enhance interpretability.

Findings and discussion

This section presents the empirical findings obtained from the analysis of the institutional academic staff evaluation dataset covering the years 2018–2024. The findings are objectively reported and supported by visualisations from the PowerPoint presentation. Subsequently, the results are interpreted and discussed in relation to the existing literature on learning analytics, student feedback, and digital quality assurance in higher education.

The longitudinal development of academic staff performance scores shows a clear, systematic upward trend from 2018 to 2024. As illustrated in Fig. 1, the average faculty rating steadily increases across the observed period, reflecting continuous improvement in teaching quality, student engagement, and institutional quality assurance mechanisms.

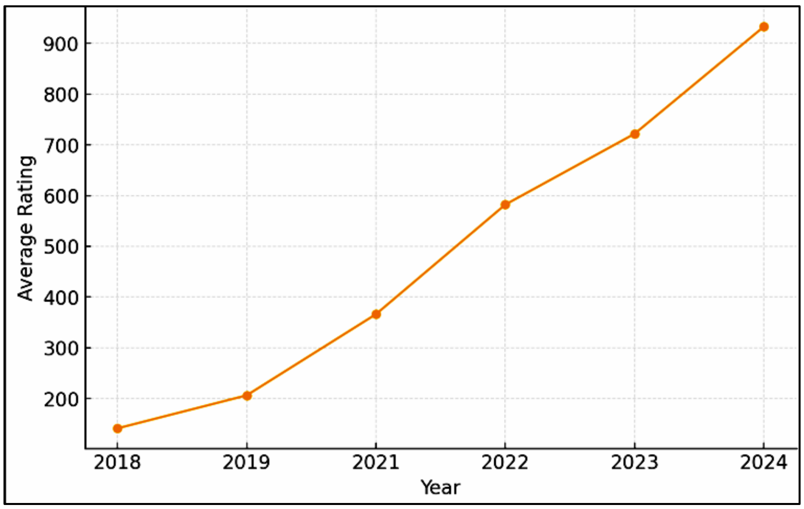

Fig. 1. Average faculty rating trend (2018-2024)

The median values also increase consistently, indicating that performance growth is not limited to a small elite group but extends to the entire academic staff. Furthermore, the widening distribution over time suggests that the evaluation system has become increasingly sensitive to performance differences. The emergence of a growing number of upper-range outliers indicates the formation of a group of exceptionally high-performing faculty members.

These findings are consistent with the literature emphasising that digitally institutionalised performance monitoring systems encourage continuous professional development and instructional innovation (Daniel, 2015; Siemens & Gasevic, 2012). The observed upward trend confirms Hypothesis H2 and demonstrates that the academic staff evaluation system at ASPU has evolved into a stable, development-oriented instrument of digital governance.

The inter-year correlation heatmap shown in Fig. 2 indicates a progressive increase in correlation coefficients from year to year. High correlations observed during the 2021–2024 period (r ≈ 0.80–0.90) confirm that the rating system has reached a mature, stable institutional structure. In contrast, relatively weaker correlations between 2018 and 2019 indicate an early transition phase in the calibration of the digital evaluation system.

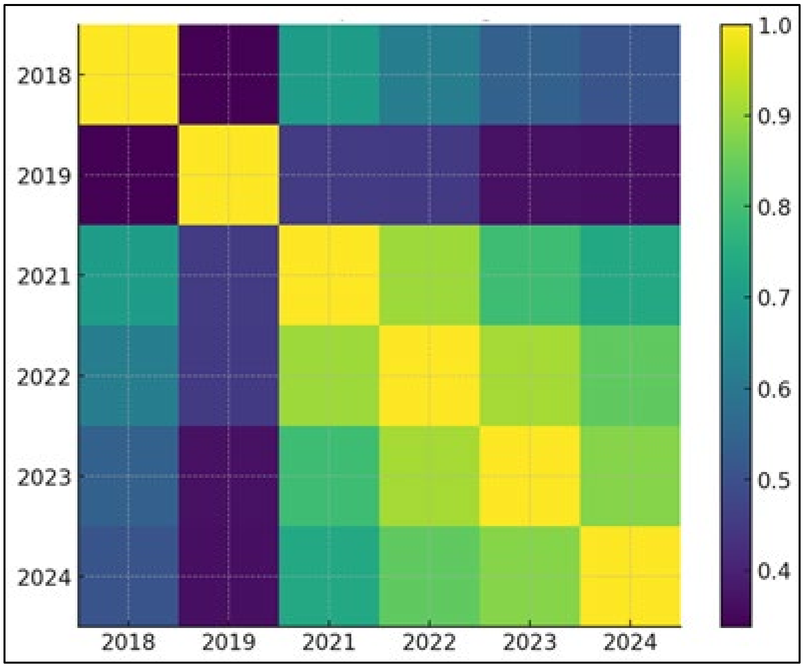

Fig. 2. Correlation heatmap of rating (2018-2024)

This stabilisation process aligns with theoretical models of digital system institutionalisation, which emphasise the importance of organisational learning and regulatory alignment during early implementation phases (Schildkamp et al., 2013). The results empirically validate Hypothesis H6 and confirm that the evaluation model has achieved high predictive reliability.

The frequency distribution of rating scores shown in Fig. 3 exhibits a pronounced right skew. The majority of faculty members are concentrated within the 0–1500 range, indicating a broad, stable performance band. At the same time, a long right tail indicates the existence of a limited number of exceptionally high-performing academics.

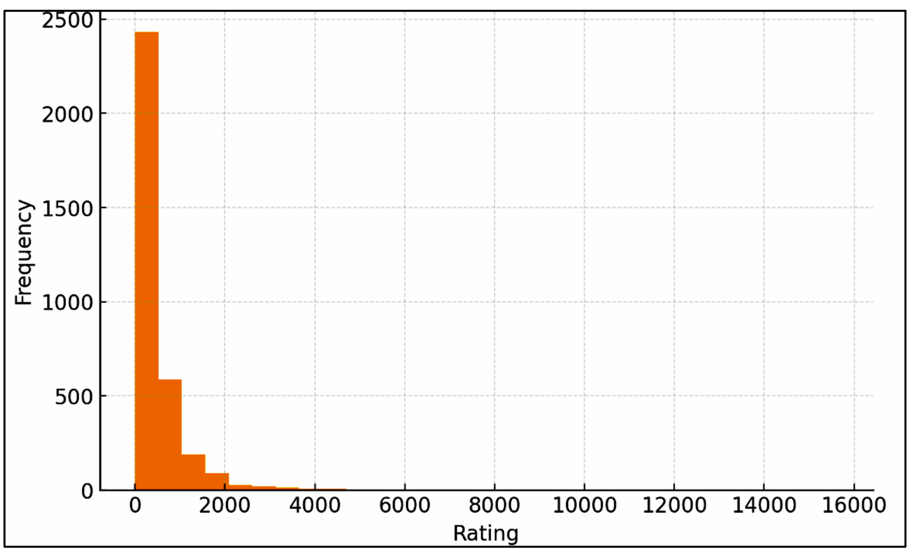

Fig. 3. Overall distribution of academic rating scores (2018-2024)

Such distributional characteristics indicate that the system simultaneously stabilises general academic performance while maintaining sensitivity to elite professional excellence. Similar performance clustering effects in digital evaluation systems have been reported by Wilsdon et al. (2015) in their analysis of metric-based academic governance.

The gender-based comparative analysis shown in Fig. 4 indicates that female faculty members consistently receive slightly higher average rating scores across most academic years. However, both male and female performance indicators exhibit a steady parallel upward trend, and the observed gender gap remains small but stable.

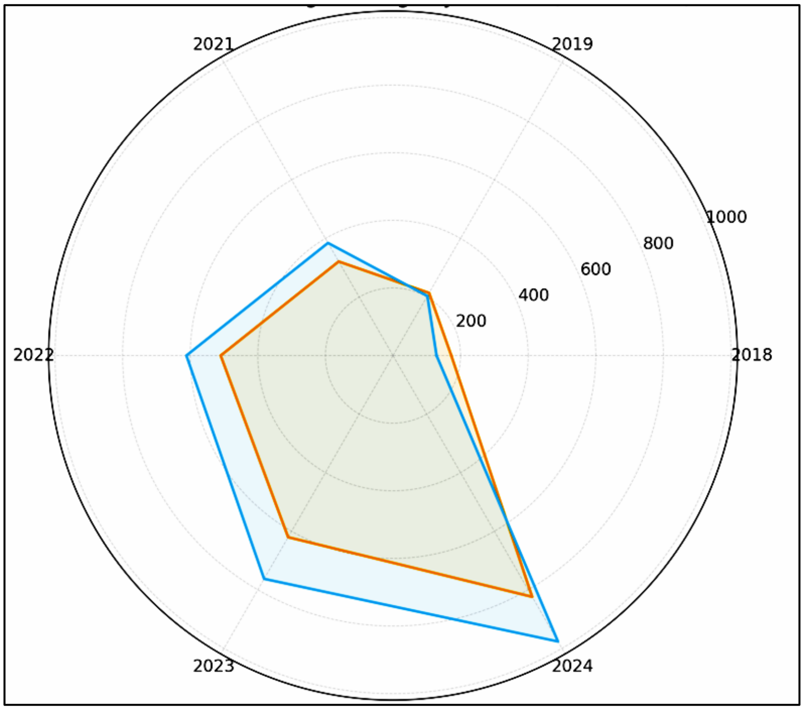

Fig. 4. Average ratings by gender (2018-2024): red line – male, blue line - female

The persistence of higher average performance among female faculty may reflect differences in instructional engagement, responsiveness to feedback, and student-centred teaching approaches, as discussed by Spooren et al. (2013). These findings empirically support Hypothesis H3 and indicate a balanced and inclusive institutional performance environment.

Age-based performance trajectories presented in Fig. 5 indicate that the 30–39 age group exhibits the most significant performance growth and achieves the highest average rating scores by 2024. The 40–49 and 50–59 groups exhibit stable, continuous increases in performance, whereas the 60+ group shows slower growth. The <30 group improves progressively but remains at a lower baseline due to early career positioning.

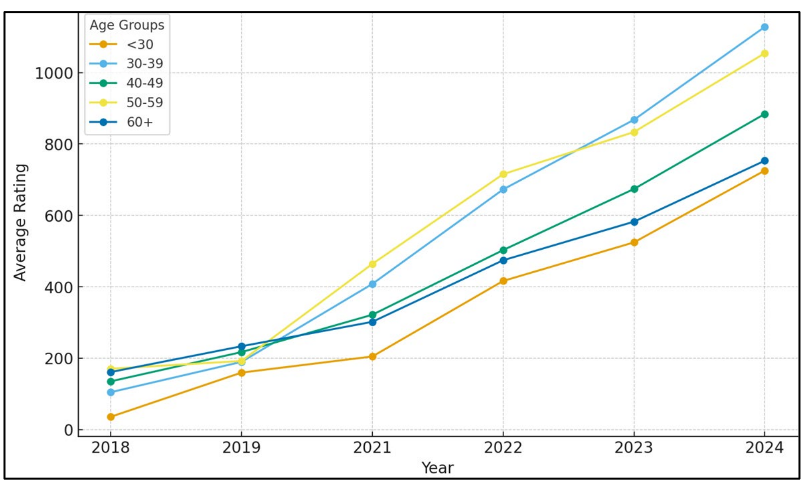

Fig. 5. Average rating trends by age groups (2018-2024)

These dynamics reflect classical academic career development patterns, where early-career faculty gradually build performance capacity, mid-career faculty reach peak productivity, and senior faculty maintain stable contribution levels. The findings strongly support Hypothesis H4 and align with previous results on academic performance life cycles.

The scatter plot in Fig. 6 shows a strong positive linear relationship between student feedback scores and composite academic staff ratings. Faculty members with 90–100% feedback consistently achieve the highest performance ratings, while instructors in the 50–70% feedback range predominantly remain within the lower rating intervals.

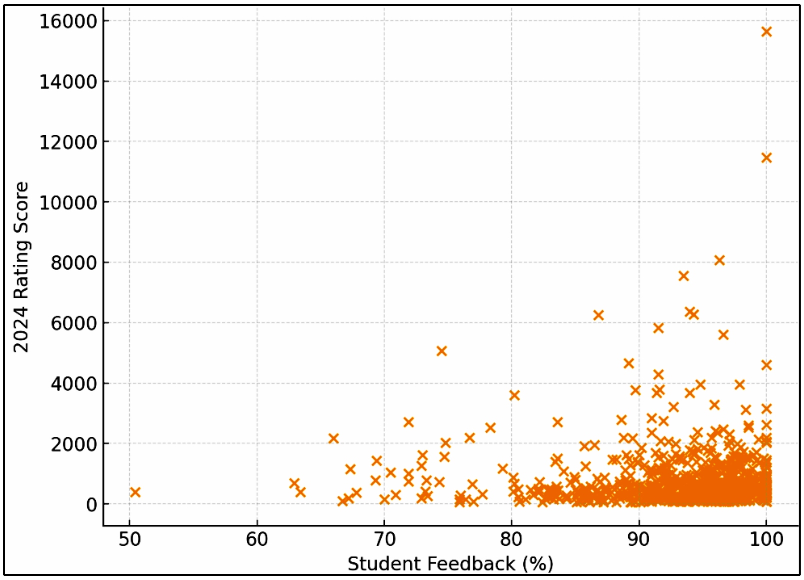

Fig. 6. Student feedback and 2024 rating

These results provide strong empirical support for Hypotheses H1 and H5, confirming that student feedback functions as a structural predictor of academic performance rather than merely as an indicator of satisfaction. This finding is consistent with large-scale validation studies on the predictive validity of student evaluations of teaching (Spooren et al., 2013).

The feedback distribution shown in Fig. 7 indicates that the vast majority of feedback scores fall within the 90–100% range, indicating high overall student satisfaction. The distribution is right-skewed, with only a small number of instructors located in the lower satisfaction range (50–70%).

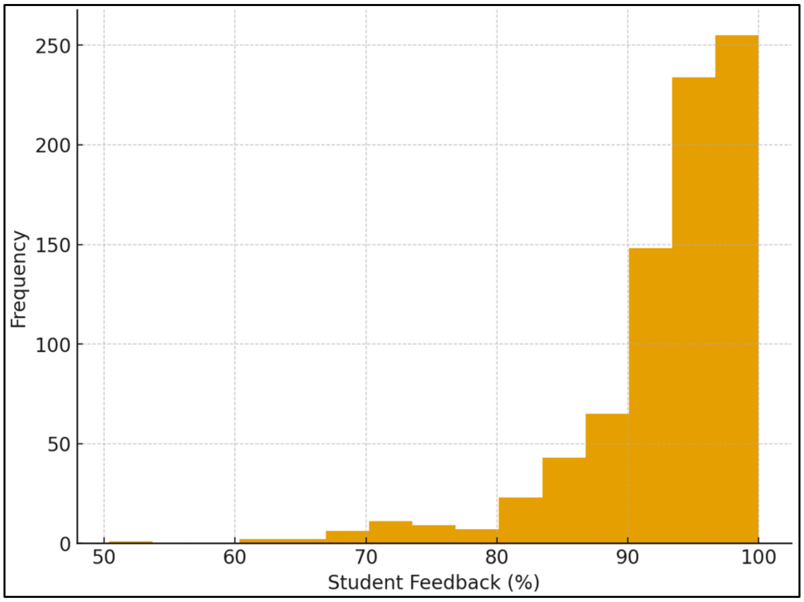

Fig. 7. Distribution of student feedback scores 2024

This pattern indicates that the teaching environment at ASPU is generally favourable. The small group of low-feedback outliers may be a suitable target population for targeted pedagogical support and intervention programs.

The overall rating distribution in Fig. 3 indicates that most academic staff are concentrated in the middle performance band, particularly in the 0–1500 range. This distribution creates a structurally stable and broad “middle mass”. Fig. 4 shows that female teachers have slightly higher average ratings than men, and their performance distribution is denser and more stable. Analysing these two visuals together reveals the following results:

First, the slight advantage of female teachers does not contradict the overall distribution in Fig. 3; instead, the higher median score of women in Fig. 4 explains the concentration of the central mass in Fig. 3 in the stable medium-high performance zone. That is, the results for female teachers are both more tightly clustered and less dispersed, indicating more stable performance.

Second, there is more variability in the performance curve for men. This is consistent with the wide dispersion in Fig. 3. That is, there is a larger mass of both high and low performers among men. This heterogeneity is also confirmed by the more playful performance curve for men in Fig. 4.

Thus, Fig. 3 and Fig. 4 together show that female teachers exhibit a performance structure consistent with a “stable medium-high performance model”. In contrast, male teachers exhibit a performance structure consistent with a “wide variability model”.

The overall rating distribution shown in Fig. 3 indicates that most academic staff are concentrated in the average performance range. When analysing this distribution, accounting for performance dynamics by age group in Fig. 5 enables a more accurate interpretation of the performance structures. The interpretation of both visuals together is formed as follows:

First, the <30 age group starts the rating at a low level, and the distribution of this group in Fig. 3 essentially corresponds to the lower segment. This is explained as a natural consequence of the early-career stage: teachers have not yet gained experience and have not yet developed a portfolio of academic activities.

In contrast, the 30–39 age group has both the fastest growth dynamics in Fig. 5 and is the primary “carrier” of the right-sloping high-performance tail observed in Fig. 3. The sharp increase in the performance of this group indicates that they have already entered the peak of productivity in terms of both pedagogical and scientific activity. This age group plays the role of the “main driving force” in the university rating system.

The 40–49 age group exhibits a stable, rising trajectory in performance. Their location in Fig. 3 is more consistent with the middle mass. Since this group is at a mature stage in both experience and methodological mastery, the rating distribution is characterised by stability and reliable performance.

The 50–59 age group also shows an increasing but more moderate dynamic. Their representation in the middle of the right tail in Fig. 3 indicates a combination of extensive years of experience and stable, high performance. In this group, variability is minimal, and the results are consistent.

Finally, the 60+ age group shows a slower rate of growth and aligns with the lower-ranking segment in the distribution in Fig. 3. This is a natural feature of the career stage, as performance growth continues in a more stable, rather than dynamic, manner.

Thus, the right-skewed structure of the rating distribution in Fig. 3 is attributable to the high dynamism of the 30–39 age group and the stable, high performance of the 40–49 age group. The 20–30 and 60+ age groups are located in the lower and middle parts of the overall distribution, confirming that performance heterogeneity is related to the natural career cycle.

When Fig. 6 and Fig. 7 are considered together, parallel and mutually complementary findings emerge, confirming that student feedback is a key structural predictor of teacher performance. The comparative observations presented in the table can be interpreted in academic terms as follows:

First, Fig. 6 shows a strong positive linear relationship between student feedback and academic ratings: teachers who receive high levels of student feedback consistently receive higher ratings. These data suggest that student satisfaction is not merely an emotional construct but a direct indicator of the quality of a teacher’s instruction, course organisation, and pedagogical effectiveness. Thus, empirical evidence confirms that student feedback is a reliable predictor of academic performance.

The distribution of student feedback in Fig. 7 complements this relationship. The figure shows that most of the input falls within the 90–100% range, indicating a right-skewed distribution and generally high student satisfaction. The relatively small number of teachers receiving low feedback accounts for the presence of a small risk group concentrated in the low-rating segment in Fig. 6. It is easier for this group of teachers to implement targeted methodological support and professional development programs, since they are not numerous and the problem is clearly identifiable.

Together, these two figures reveal a broader conclusion: the high ratings of teachers who receive high feedback are not just a random coincidence, but a systematic and persistent trend. On the other hand, the high and dense distribution of student feedback (Fig. 7) suggests that the teaching environment at the university is generally positive and that students rate the vast majority of teachers highly. In parallel, the low feedback-low rating relationship in Fig. 6 strengthens the psychometric validity of student feedback as a measurement tool.

Thus, the mutual analysis of the two visualisations shows that student feedback is not merely an additional indicator in the ASPU academic assessment system, but a structured, stable, and predictive component of teacher performance. This result is entirely consistent with both the international literature and the theoretical foundations of digital monitoring systems.

It contrasts four key indicators that demonstrate how ASPU's digital academic assessment system has matured over the years: long–term growth in ratings, stability of inter-year correlations, the predictive value of student feedback, and the structure of overall student satisfaction. Each of these indicators and the results they produce at the system level can be explained as follows:

The first indicator, the annual rating increase observed in Fig. 1, confirms that teacher performance is not just temporary but shows a consistent and sustainable increase. The increases in both the average and median ratings over the years indicate a broad-based development process among the academic staff. This result suggests that the system has already become a management tool capable of creating behavioural changes, thereby having a real impact on teachers' teaching, research, and service activities.

The second indicator, the high inter-annual correlation shown in Fig. 2, indicates that the system measurements have stabilised and the results can be reliably replicated, especially since 2021. A high correlation indicates strong agreement in measuring teachers' performance indicators across two consecutive years, indicating that the assessment tool is no longer susceptible to random variation and operates on a stable methodological basis.

The third indicator, the predictive role of student feedback on academic performance, as determined in Fig. 6, indicates the high psychometric quality of the system. The finding that academic ratings increase with student feedback confirms the structural validity of the digital assessment model. This means that the system not only conducts statistical monitoring but also uses relevant and meaningful variables to measure the quality of teacher instruction.

The fourth indicator, the high and stable student satisfaction observed in Fig. 7, indicates that the overall learning environment is favourable. The fact that the vast majority of student feedback is collected in the high range indicates both the quality of the learning process and the strength of student-teacher interaction. This structure strengthens the system's internal balance and fosters a conducive pedagogical environment for teacher development.

Together, these four indicators demonstrate that ASPU's digital academic assessment system is not merely a data-collection mechanism but a mature, sustainable, and reliable management tool. The system both stimulates performance growth and provides a stable, predictable basis for institutional decision-making.

The overall rating distribution shown in Fig. 3 exhibits a right-skewed tail in academic staff performance, indicating that high-performing teachers are concentrated at the right end. This structure suggests that an “elite high-performance group” has formed within the university. This group demonstrates remarkable results in research, pedagogical quality, and social and institutional services. Such a right tail is the most typical indicator of performance heterogeneity, indicating that the system can distinguish not only average results but also individual preferences.

Second, Fig. 4 shows the performance differences by gender. The figure shows that the average performance of female teachers is slightly higher than that of male teachers and exhibits a more stable trajectory. This suggests that performance heterogeneity is also observed across gender. As highlighted in the table, a more stable pattern of medium-to-high performance has emerged among female teachers. In contrast, a broader range of performance is observed among males, including both very high and relatively low results. This wide variation indicates that heterogeneity is more substantial among males.

Third, Fig. 5 presents performance dynamics across age groups and indicates how heterogeneity is associated with career stages. Here, the 30–39 age group shows the most significant increase in performance, and the right tail (high-performing group) appears to be primarily composed of this group. The 40–49 age group shows stable, high performance, whereas the 50–59 age group shows similarly stable but more gradual increases. The <30 and 60+ age groups are more represented in the lower and middle parts of the overall distribution.

Thus, these three indicators together confirm that the system can measure not only overall performance but also its internal structure, stratification, and diversity. Performance heterogeneity is closely related to individual characteristics (e.g., gender), career stages (e.g., age), and individual development rates within the broader academic environment. This indicates that the rating system has both the potential for differential assessment and the power to support decision-making in institutional management.

Overall, the findings demonstrate that the academic staff evaluation system at ASPU exhibits:

- Strong longitudinal stability,
- High predictive reliability after institutional calibration,
- A robust structural relationship between student feedback and academic performance,
- Statistically meaningful performance differences across gender and age groups.

These results confirm that the learning analytics-based evaluation system has evolved into a mature digital quality assurance mechanism that not only monitors academic performance but also actively regulates professional development dynamics within the institution.

Conclusion

This study examined the relationship between student feedback, composite academic staff rating scores, and demographic variables within a learning analytics-based evaluation system using longitudinal data from 565 faculty members (2018–2024). The findings reveal a consistent upward trend in academic staff performance and confirm that student feedback is a strong structural and predictive determinant of overall academic performance. Gender- and age-based analyses indicate that female faculty members demonstrate slightly higher average performance, while the 30–39 age group exhibits the strongest performance dynamics. Inter-year correlation results indicate that the digital evaluation system exhibited high institutional stability and predictive reliability after 2021. Overall, the findings confirm that learning analytics-based academic staff evaluation systems function as continuous, data-driven, and development-oriented quality assurance mechanisms that support sustainable academic quality and evidence-based governance in higher education.

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