Personalized Feedback in University Contexts: Exploring the Potential of AI-Based Techniques

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Personalized feedback in university contexts: exploring the potential of AI-based techniques

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Abstract. Many recent studies highlighted the importance of feedback on the quality of learning. It empowers students to take ownership of their learning, fosters engagement and motivation, and enables personalized learning experiences. However, the use of feedback processes in real-world everyday teaching often becomes unsustainable, due to the number of students and the timing of the courses, especially in university contexts. The present study aimed to address this challenge in real university classes, laying the groundwork for the future development of an automated intelligent system that can support university teachers in delivering personalized feedback to a large group of students in real-world environments. Specifically, it focused on the prospect of gathering quality data from an actual academic course, intending to appropriately fuel AI-based techniques. These techniques could enhance the comprehension of students' learning evidence and offer valuable insights to teachers. This paper presents an experimental work, carried out in the academic year 2020/21, which involved 220 students attending the first year of the Master's Degree course in Primary Education. The components of teachers' professional vision were explored using a rubric developed by the research team. Preliminary results suggested that the rubric can be effective in capturing sequential information about students' development of professional vision. Thus, it can be further exploited to collect data from the process and feed AI-based algorithms. Further developments include exploring other machine learning techniques to reduce observers' bias and support teachers in providing more effective personalized feedback.

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Keywords: feedback, university, AI-based techniques.

1 Introduction

Many recent studies highlighted the importance of feedback on the quality of learning [1; 2; 3]. It empowers students to take ownership of their learning, guides institutions in making informed decisions, ensures continuous improvement, fosters engagement and motivation, facilitates open communication, and enables personalized learning experiences [4]. However, despite its relevance, the use of feedback processes in everyday teaching often becomes unsustainable, due to the number of students and the timing of the courses, especially in university contexts. On the other hand, the expansion of ubiquitous learning in digital environments has led to an exponential growth of significant data for tracking learning. Although the use of these data can be beneficial, tools and technologies are needed for automated data collection and analysis [5].

In this direction, significant support can be provided by technologies incorporating Artificial Intelligence (AI), which include a wide collection of different technologies and algorithms [6]. Notably, Learning Analytics (LA) [7] and Educational Data Mining (EDM) [8] can be useful in developing a student-focused strategy [6; 9]. The systematic use of AI techniques and algorithms could enable new scenarios for educators, profiling and predicting learning outcomes and supporting the creation of sustainable patterns of assessment [10]. However, even though several studies aimed at integrating EDM and LA techniques in online learning environments [11], only a few of them focused on applying them to real-world physical learning environments to support teachers in providing timely and quality feedback based on minimally invasive measurements [12; 13].

The present paper presents an approach to address the feedback problem in real university classes, laying the groundwork for the future development of an intelligent system that can inform and support the university teacher in delivering personalized feedback to a large group of students in real-world environments. The project has been designed in cooperation between the Department of Education, Cultural Heritage and Tourism of University of Macerata and LabMACS of Università Politecnica delle Marche.

Specifically, we present an experimental work carried out during the academic course of "Didattica Generale" at the University of Macerata in the academic year 2020/21. We involved 220 students attending the first year of the Master's Degree course in Primary Education and we traced the development of their professional vision, focusing on the main components of noticing and reasoning. These components were explored and assessed at various times by means of a questionnaire and the related rubric purposely developed by the research team.

These were the questions that led the research:

- what kind of data can we collect from the educational processes that take place during traditional lessons in the real-world environment?
- how can the university teacher use these data to provide feedback and improve students' learning outcomes?

This contribution is structured as follows: paragraph 2 briefly outlines a theoretical background concerning feedback at university and possible contribution of AI-based techniques; paragraph 3 describes the experimental work, providing details on the context and participants and the professional vision model; paragraph 4 presents the assessment tools and data analysis methodologies. Finally, paragraph 5 reports the preliminary results, while paragraph 6 discusses them and draws conclusions and further developments.

2 Theoretical background

2.1 Feedback in University

For many years, literature has highlighted the crucial role of feedback as a learning mechanism in the assessment process [14;15]. Feedback can be a supporting tool for meaningful and deep learning, which is not a mere assimilation of contents, but a mobilization of skills and assumption of postures, especially useful in university courses aimed at professionalization [16].

Recent research developments in the field of feedback have shown a shift from a more transmissive model [17] to a socio-constructivist one that conceives feedback as a dialogic process through which learners actively construct, monitor, and assess their learning [18;19]. The new learning-centred approach to feedback [20; 3; 21] emphasizes the interactions between students and university teachers, the active and personal interpretation, and the transformative use by the students also in terms of self-improvement and self-regulation [22].

In contemporary university education, the function of feedback thus changes from a simple exchange of questions and answers between teachers and students to a circular, generative, and self-poietic process [23], becoming «a process in which students are proactive in seeking, making sense of and using feedback on their performance or approaches to learning» [3, p. 6].

This new assessment framework, coherently with the assessment *as* learning paradigm, focuses on the feedback process rather than on the object of assessment, i.e. on the quality and how the teacher provides feedback and how students interact, analyze, discuss, and then use it to improve the task and, more generally, their own learning path.

Learners' engagement in feedback processes, as one of the key elements of the learning-oriented assessment paradigm [1], seems to stimulate a more effective understanding and application of knowledge [24] and, more importantly, the acquisition of assessment skills over time [19; 15]. According to Carless [25], the most powerful feedback is that which has a long-term dimension, generating thought, reflection, and subsequent thoughtful action. To enable assessment to become a strategic process through which students can improve their learning, it needs to be concretely integrated with the learning process, enhancing the role and use of feedback to promote students' skills and awareness of the meaning of assessment and the use of appropriate assessment strategies [26].

Feedback processes allow teaching action to be rethought in an integrated way, promoting different forms of planning and management of teaching/learning paths that include assessment, motivation, self-regulation, and reflection [27].

The rethinking of the goals of assessment and feedback runs parallel to that concerning educational practices, promoting new and 'different' synergies between ends and means and new strategies and models of action. At the same time, this change encourages reflection on the support that technologies can currently offer in terms of accuracy, sustainability, and timeliness [28].

Indeed, the widespread recognition of feedback's relevance for learning often clashes with the pervasiveness of low-quality feedback in higher education [29], due to unclear expectations and lack of timeliness, usefulness, and comprehensibility [30; 31]. In large class sizes, as those in university contexts, managing and providing timely and effective feedback to engage students in meaningful learning experiences can be undoubtedly challenging [32], underlining the growing need for automated feedback tools and technologies.

The field of Learning Analytics (LA) is one of the approaches that could provide a solution to the state of feedback in higher education. LA researchers are actively exploring automated feedback solutions that can enable teachers to deliver effective feedback and improve the speed of feedback delivery to students [33].

However, the effective integration of technologies, as in the case of AI-based systems, requires a process of interaction with the automated agents themselves. This point is particularly relevant for university teachers who deal with new data-driven systems since they need to rethink pedagogical and didactic approaches and undertake a process of progressive learning and professional development [34].

2.2 AI-based techniques to support feedback

Please AI in education spans various domains, encompassing machine learning (ML), which employs algorithms to identify patterns in educational data through iterative training; deep learning, utilizing extensive datasets to simulate and predict educational outcomes; and natural language processing (NLP), employing algorithms for language recognition to extract and analyze textual meaning [35; 36; 37].

Within education, AI can bolster learning environments by incorporating automated, data-driven, personalized feedback, which holds the potential to improve student learning outcomes as well other learning features (e.g., interest, performance, etc.) [36; 38]. Notably, AI research in the education sector necessitates an interdisciplinary approach that integrates diverse fields, including engineering and education.

Diverse tools and technologies play a crucial role in automating the collection and analysis of data [5]. In this context, considerable assistance can be derived from technologies that incorporate AI [6]. Notably, LA [7] and EDM [8] can prove valuable in formulating a student-centric approach [6; 9]. The systematic application of AI techniques and algorithms has the potential to unlock new possibilities for educators, enabling the profiling and prediction of learning outcomes and facilitating the development of sustainable assessment patterns [10].

However, despite being an emerging field in educational technology for approximately 30 years, educators still face uncertainty about how to effectively leverage AI techniques on a broader scale for pedagogical advantages and meaningful impacts on teaching and learning in higher education [39].

Recent trends in research within this domain highlight that researchers are exploring the potential application of AI also in the physical classroom settings [36; 12; 13] and devoting efforts to identify detailed entailment relationships between learners' responses and the desired conceptual understanding mostly within intelligent tutoring systems [36; 11; 9; 6].

It should be noted that different types of educational environments, such as traditional classroom education, computer-based learning or blended education, and the information systems employed, such as Learning Management System, Intelligent Tutoring System, or Massive Open Online Course, etc., allow for the collection of diverse data to address various educational challenges [5]. For instance, educational data can be obtained from real-world interactions during events or classroom activities, as in Screpanti, Scaradozzi, Gulesin, and Ciuccoli [13], or from e-learning activities, as in Kochmar and colleagues [38]. The challenging tasks of gathering and integrating raw data from diverse environments involve searching for new tools and methods to search for patterns and support data-driven decision-making by merging technical, social, and pedagogical dimensions of learning. The ultimate overarching aim is to enhance educational practices through data-intensive approaches to educational research, thus it is essential to emphasize that the gathered data must be quality data. Ensuring high data quality before executing any AI-based algorithm is a pivotal stage in the broader workflow. Moreover, utilizing data of inferior quality can significantly compromise the outcomes and result in consequential implications when decisions are based on those results, like assisting teachers in delivering timely and quality feedback.

3 The experimental work

In the academic year 2020/21 we carried out preliminary and experimental work which involved 220 students attending the first year of the Master's Degree course in Primary Education at the University of Macerata. Specifically, the experimental work was conducted during the academic course of "Didattica Generale", consisting of 48 hours of lectures and 20 hours of workshop with compulsory attendance.

The course aims to provide the theoretical basis on Didactics and the processes of learning and teaching, supporting students in the development of knowledge, abilities, and skills that will constitute the foundation of their teaching professionalism. To this end, the course is structured in interactive lectures and workshops based on moments of exchange, small group work, and guided and modeling activities focused on the critical analysis of teaching practices.

During the second semester, the students attended lectures and took six tests structured in the same way. Each test required students to watch and analyze a video, lasting approximately 10-15 minutes, which was recorded in an Italian primary school showing a real classroom situation with teacher-student interactions.

After watching each video, the students filled in the same questionnaire, administered via Google forms. This form consisted of open-ended questions relating to five dimensions defined by the team of researchers according to the course content and the Seidel and Stürmer's model [40].

3.1 Professional vision model

In the training of future teachers, the ability to analyze different teaching interactions by describing, explaining, and predicting, is considered a key competence of teacher professionalism [41; 40], as confirmed by the literature on the professional vision of future teachers.

The professional vision includes the ability to notice and interpret relevant features of classroom situations [42] and represents an important element of teacher expertise to be developed during teacher education. Future teachers, at the beginning of their university-based education, often struggle to focus on relevant elements of classroom situations to select events that can influence student learning [43]. Therefore, one of the key aims of future teacher education is to systematically foster the acquisition of integrated knowledge [40].

In this direction, Seidel and Stürmer [40] defined a model operationalizing professional vision, with a focus on university-based teacher education, starting from its two main subcomponents: noticing and reasoning (see Fig. 1).

According to the authors, noticing describes whether future teachers pay attention to events that are relevant for teaching and learning in classrooms (e.g., influencing student learning positively or negatively). Even in short sequences of classroom situations, future teachers can note several teaching and learning acts, that are more or less important. Thus, the events to which teachers focus during the observation of a classroom sequence serve as a first indicator for the activation of teacher knowledge. Noticing aims to prompt the teacher's knowledge by the selection of classroom events and refers to three substantial components of the teaching and learning action, stemming from the model of Seidel and Shavelson [44]:

- learning climate: as an indicator for the motivational-affective classroom context;
- goal clarity and orientation: as an indicator for the successful preparation of learning;
- teacher support and guidance: as a guiding process involved in the execution of learning activities.

Reasoning refers to the ability to take a reasoned approach to events noticed in the classroom and focuses on the main aspects and processes involved in the analysis of teacher-student interactions by future teachers. Research distinguishes three qualitatively different but highly interrelated aspects of the teachers' reasoning [45]:

- description: the ability to clearly identify and describe the relevant aspects of a noticed teaching and learning component (i.e., goal clarity) without making any further judgments;

- explanation: the ability to use what one knows to reason about situations, and classroom events, according to professional knowledge and the components of teaching involved;
- prediction: the ability to predict the consequences of observed events in terms of student learning, drawing on broader knowledge about teaching and learning as well as its application to classroom practice.

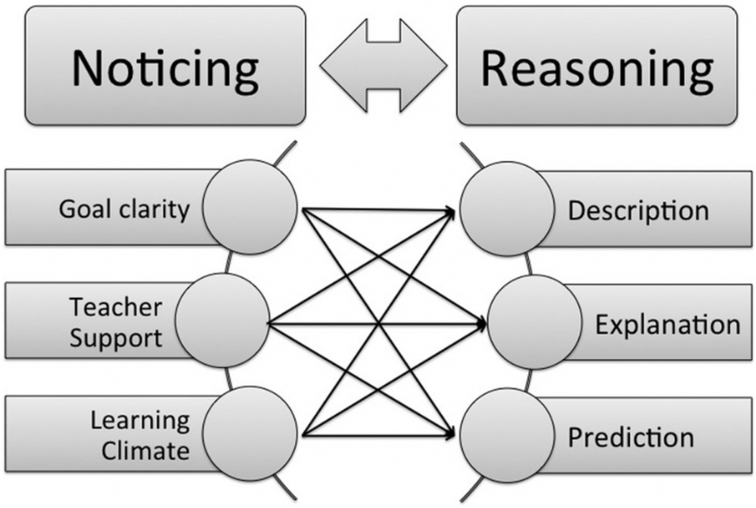

Fig. 1. Noticing and reasoning as two components of professional vision [40, p. 744].

4 Methods

4.1 The questionnaire

As mentioned before, students' understanding and learning were tested during the course at six different times (t1-t2-t3-t4-t5-t6) to assess and support the development of noticing and reasoning skills.

The open-ended questions concerning the six videos related to the following five dimensions:

1. Bridge and Conflict: refer to the recall of the students' formal and informal knowledge as a "bridge" to deal with the challenging situation presented, the cognitive conflict underlying this situation [46], and how they take students' culture (equity) into account;
2. Outcome: refers to the objectives (micro-macro goals), aims (horizon of meaning), and skills the students work on through the observed activity;
3. Mediators: refers to the four types of mediators described by Damiano [47], how they are used to address the conflict, and the functional arrangement of the environment;

4. Assessment: refers to the four types of interactions defined by Altet [48] used by the teacher to manage interaction and classroom climate, the feedback provided, and any possible important elements to assess the activity;
5. Lesson management: refers to the initial and final phase of the lesson (introduction and debriefing).

These dimensions cover the key concepts and subconcepts addressed in "Didattica Generale" lectures and workshops and taken up in other lectures, internships, and workshops throughout the five-year University course, as core aspects of teaching practice. Moreover, each dimension refers to one or two of the components defined in Seidel & Stürmer's model (goal clarity and orientation, teacher support and guidance, and learning climate) (see Table 1).

Table 1. Dimensions, open-questions, variables.

Dimensions	Questions	Variables
Bridge and Conflict *(goal clarity and orientation - teacher support and guidance)*	*How does the teacher take students' (formal and informal) knowledge into account?*	V1
	What is the cognitive conflict underlying the challenging situation?	V2
	How do they take the student's culture (equity) into account?	V3
Outcome *(goal clarity and orientation)*	*What objectives are present?*	V5
	What aims are present?	V6
	What skills does the student work on?	V7
Mediators *(teacher support and guidance)*	*What mediators are used?*	V9
	What relationship exists between mediators and conflict?	V10
	How is the environment set up by the teacher to carry out the work?	V11
Assessment *(teacher support and guidance - learning climate)*	*How does the teacher manage interaction and the classroom climate?*	V8
	Are feedback between student and teacher foreseen?	
	What elements could be used for assessment?	
Lesson management *(goal clarity and orientation)*	*Is an introduction and orientation phase planned?*	V4
	Is debriefing foreseen?	

4.2 The rubric

The students' answers and textual information were processed by a team of researchers using a rubric, intentionally developed by the team. Questions became indicators and, for each indicator, the team defined 5 levels and descriptors, useful to assess the indicator. The team rated each indicator of the rubric by assigning a level on a rating scale from 1 to 5.

The resulting numeric dataset consisted of 220 cases, each of which included 11 numerical values related to the variables of the five dimensions of the rubric.

Table 2 shows an example of the rubric structuring in dimensions, indicators, levels/descriptors by reporting the excerpt for the specific dimension of Mediators.

Table 2. Excerpt of the rubric for the dimension of Mediators.

Dimension	Indicators	Level 1	Level 2	Level 3	Level 4	Level 5
Mediators	Identify the mediators used	Does not identify mediators	Identifies non-mediators materials	Identifies some mediators without connecting them with use	Identifies the most relevant mediators and their use	Identifies all mediators and their use and categories
	Describe the environment set up by the teacher to carry out the work	Describes the objects but does not grasp the link between the environment and didactic processes	Describes only the objects which are most functional to didactic processes	Describes the objects which interact / are functional to didactic processes	Describes the environment and its role on the didactic process	Describes the environment, its role on the didactic process and possible alternatives
	Identify the relationship between mediators and conflict	…				

4.3 Data analysis

The scores from the rubrics were recorded in a spreadsheet and then imported into RStudio for subsequent analysis.

The initial dataset comprised 220 cases, encompassing the four measurements at different times (t2, t3, t4, t6) of the 11 variables (V1, ..., V11) associated with the analytic rubric characterizing professional vision (Table 1).

First, the dataset preparation included a check for incomplete, duplicate, or missing answers. After this initial check, the final dataset comprised 59 cases, namely only those students who provided an answer at each of the four measurement times and received an evaluation for each submission of the assignment. The data were further processed to visually assess the effectiveness of the rubric as an assessment tool for teacher professional vision. This involved generating a radar chart to offer a quick visual measure across the four measurement times. Additionally, a box plot chart was analyzed to understand the distribution of total scores at each measurement time. Finally, the standardized variables were utilized for conducting cluster analysis through the 'cluster' package [49]. The clustering techniques implemented the kmeans algorithm; the elbow method and the gap statistics were used with the total within sum of squares to specify the optimal number of clusters to extract.

5 Preliminary results

Results from data analysis are reported in Fig. 2, 3, and 4. The radar plot (see Fig. 2) visually represents the relative contribution of each variable to the core competency of the teacher's professional vision. It offers a graphical description of the progression of the competency across the four measurement times, clearly illustrating the pattern. Notably, the area of the polygon increases from t2 to t4 and experiences a slight decrease at t6. This decrease can be explained by the higher level of complexity that characterized the final test; however, we found a reduction in the variability of total scores which can be considered a positive element.

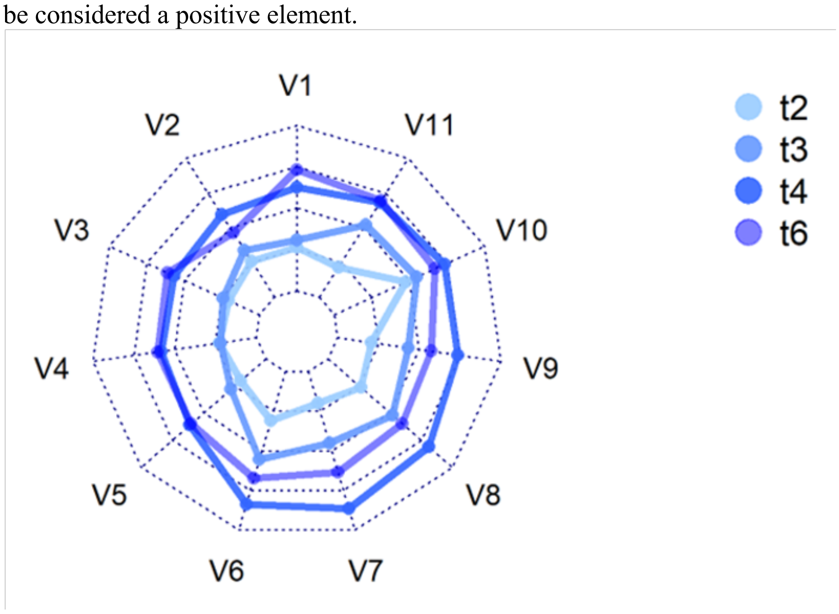

Fig. 2. Mean values of scores at different measurement times.

For a more detailed examination of this trend, Fig. 3 displays the distribution of total scores at different measurement times. The mean scores show a consistent increase from t2 to t4, followed by a decrease from t4 to t6. Examining score variability, it becomes evident that it is smaller at t6 compared to the other measurement times.

Additionally, Fig. 2 highlights that at t2 and t3 measurements, scores for V6 to V11 are higher than those for V1 to V5, whereas only at t4 and t6, the scores for V1 to V5 exhibit a marked increase.

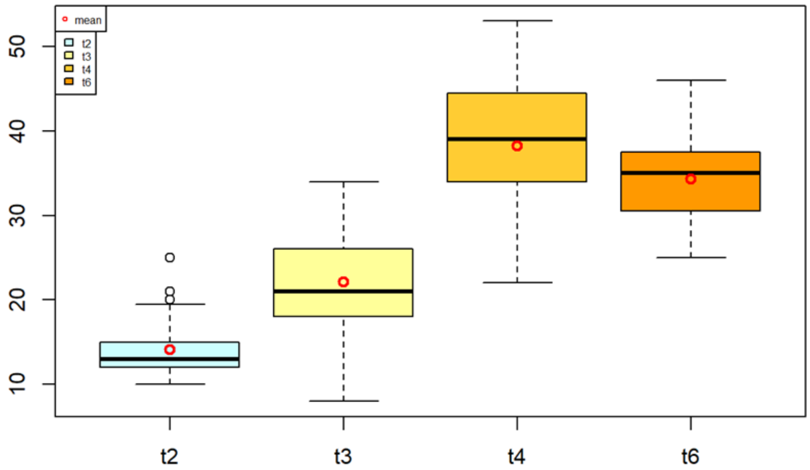

Fig. 3. Distribution of total scores at different measurement times.

Finally, the clustering procedure can offer valuable insights to the educator by presenting a comprehensive overview of the class's performance across various texts. Fig. 4 illustrates the visualization of clusters on a scatterplot that exhibits the first two principal components on the axes. Both the elbow method and the gap statistics indicated that the optimal number of clusters is three, with sizes of 19, 11, and 29. Cluster 1 encompasses the portion of students achieving high scores in each dimension during each measurement time. Cluster 2 includes the segment of students consistently reporting the lowest scores across the measurement times. Cluster 3 comprises the portion of students displaying intermediate behavior.

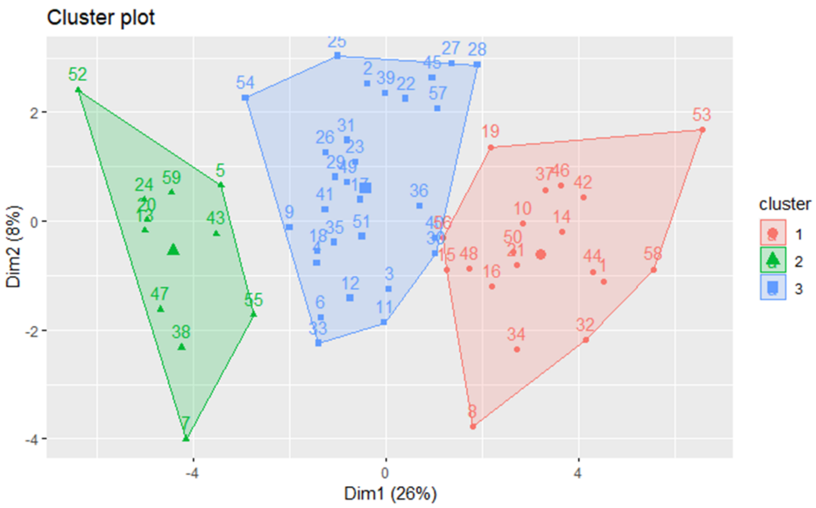

Fig. 4. Cluster plot.

6 Discussion

The current investigation focused on exploring the potential of acquiring quality data from an actual academic course designed for prospective teachers. The primary objective is to advance educational practices through the application of data-intensive methodologies in educational research, thus paving the way to effectively supporting AI-based techniques. The study specifically delved into the establishment of a metric for evaluating the competency of teachers' professional vision, a crucial aspect for future educators. The development of this metric aims to facilitate the implementation of a quantitative analysis, thus laying the groundwork for the future creation of an automated assessment technique.

Results presented in paragraph 5 showed that the rubric adequately covers the competency of the teacher's professional vision. Results clearly represent the teacher’s professional vision and align with the educational objectives of the academic course “Didattica Generale”. As it can be noted from Fig. 2, the initial high scores at t2 and t3 for V6, …, V11 and the subsequent increase of students’ scores at t4 for V1 to V5 reflects the work carried out in the classroom on the dimensions. Indeed, during the course and the workshop, we carried out guided activities of observation, description, and analysis of the teaching action that supported the growth of the students’ noticing and reasoning skills, focusing on one or more variables in each time period.

Moreover, the rubric successfully captured the state of the classroom at t6. As illustrated in Fig. 2, the area is smaller compared to t4. The mean scores in Fig. 3 depict a slight decline from t4 to t6, halting the previously observed positive trend, while the variability of scores exhibits a decrease at t6 in comparison to other measurement instances. Discussing the observed tendency in data with the experts and lecturers of the course, it was noted that it was expected because measurement at t6 was affected by the higher level of complexity that characterized the final test.

7 Conclusions

The dimensions and indicators/variables related to teaching action, defined according to the course content and Seidel & Stürmer's model operationalizing professional vision [40] seem to provide sound groundwork to analyze students' learning during the "Didattica Generale" course.

The preliminary results also showed the possibility of quantitatively analyzing data from the real-world scenario, thus laying the basis for future developments using AI-based techniques.

In this experience, the analysis is based on ratings assigned by human experts. Human intervention in the process of assessment introduces a delay in the analysis of a great number of textual assignments and results may not be exempt from raters' drift or observer's bias. Mitigation measures to avoid raters' drift could include regular training and calibration to keep raters informed, updated, and aligned with scoring expectations. Furthermore, to envision a fully automated system for supporting teachers in giving feedback, NLP and LA techniques could be combined to produce an automatic scoring system.

Future developments will delve into clustering techniques and temporal analysis, as the repeated clustering of students over time could provide the teacher with useful indications to monitor the progress of the class and provide feedback calibrated to the characteristics of the different clusters. Moreover, further directions of the present work include the study of other significant measures of student learning and the replication of the experience in future classes of the same courses.

References

1. Carless, D.: Exploring learning-oriented assessment processes. Higher Education 69(6), 963-976 (2015).
2. Hattie, J., Clarke, S.: Visible learning: feedback. Routledge, London (2018).
3. Winstone, N., Carless, D.: Designing Effective Feedback Processes in Higher Education: A Learning-Focused Approach. Routledge, London (2019).
4. Henderson, M., Ajjawi, R., Boud, D., Molloy, E. (eds.): The Impact of Feedback in Higher Education: Improving assessment outcomes for learners. Springer Nature (2019).
5. Romero, C., Ventura, S.: Educational data mining and learning analytics: An updated survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery (2020).
6. Guan, C., Mou, J., Jiang, Z.: Artificial intelligence innovation in education: a twenty-year data-driven historical analysis. International Journal of Innovation Studies 4(4), 134-147 (2020).
7. Krumm, A., Means, B., Bienkowski, M.: Learning analytics goes to school: A collaborative approach to improving education. Routledge (2018).

8. Fischer, C., Pardos, Z.A., Baker, R.S., Williams, J.J., Smyth, P., Yu, R., Slater, S., Baker, R., Warschauer, M.: Mining big data in education: Affordances and challenges. Review of Research in Education 44(1), 130–160 (2020).
9. Aldowah, H., Al-Samarraie, H., Fauzy, W.M.: Educational data mining and learning analytics for 21st century higher education: A review and synthesis. Telematics and Informatics 37, 13-49 (2019).
10. Mao, J., Ifenthaler, D., Fujimoto, T., Garavaglia, A., Rossi, P.G.: National policies and educational technology: A synopsis of trends and perspectives from five countries. TechTrends 63, 284-293 (2019).
11. Dogan, M.E., Goru Dogan, T., Bozkurt, A.: The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. Applied Sciences 13(5), 3056 (2023).
12. Scaradozzi, D., Cesaretti, L., Screpanti, L., Mangina, E.: Identification and Assessment of Educational Experiences: Utilizing Data Mining With Robotics. IEEE Robotics & Automation Magazine 28(4), 103-113 (2021).
13. Screpanti, L., Scaradozzi, D., Gulesin, R.N., Ciuccoli, N.: Control Engineering and Robotics since Primary School: an Infrastructure for creating the Digital Twin model of the Learning Class. IFAC-PapersOnLine 55(17), 267-272 (2022).
14. Hattie, J., Timperley, H.: The power of feedback. Review of Educational Research 77(1), 81-112 (2007).
15. Price, M., Handley, K., Millar, J., O'donovan, B.: Feedback: all that effort, but what is the effect?. Assessment & Evaluation in Higher Education 35(3), 277-289 (2010).
16. Laici, C., Pentucci, M.: Developing university students' feedback literacy through peer feedback activities. Education Sciences & Society 14(1), 204-222 (2023).
17. Brown S. (2014). What are the perceived differences between assessing at Masters level and undergraduate level assessment? Some findings from an NTFS-funded project. Innovations in Education and Teaching International 51(3), 265-276.
18. Grion, V., Serbati A.: Valutazione sostenibile e feedback nei contesti universitari. Prospettive emergenti, ricerche e pratiche. Pensa Multimedia, Lecce (2019).
19. Nicol, D.: From Monologue to Dialogue: Improving Written Feedback Processes in Mass Higher Education. Assessment & Evaluation in Higher Education 35(5), 501-517 (2010).
20. Molloy, E., Boud, D., Henderson, M.: Developing a learning-centred framework for feedback literacy. Assessment & Evaluation in Higher Education 45(4), 527-540 (2020).
21. Winstone, N., Boud, D.: The need to disentangle assessment and feedback in higher education. Studies in Higher Education 47(3), 656-667 (2022).
22. Laici, C.: Ecosistema formativo integrato digitale e feedback nella didattica universitaria. In: Dipace, A., Fornasari, A., De Angelis, M. (eds.) Il post digitale. Società, Culture, Didattica, pp. 147-160. FrancoAngeli, Milano (2022).
23. Laici, C., Pentucci, M.: Feedback in university didactics through One Minute Paper tool. In: Gómez Chova, L., López Martínez, A., Candel Torres, I. (eds.) ICERI2021 Proceedings, 1, pp. 1531-1540. IATED Academy, Valencia (2021).
24. Orsmond, P., Merry, S., Reiling, K.: Biology Students' Utilization of Tutors' Formative Feedback: A Qualitative Interview Study. Assessment & Evaluation in Higher Education 30(4), 369-386 (2005).
25. Carless, D.: Feedback loops and the longer-term: towards feedback spirals. Assessment & Evaluation in Higher Education 44(5), 705-714 (2019).
26. Grion, V., Serbati, A., Doria, B., Nicol, D.: Rethinking feedback: The role of comparison in assessment for learning processes. Education Sciences & Society, 12(2), 205-220 (2021).

27. De Angelis, M., Bruni, F., Petti, L.: Developing feedback literacy in initial teacher education: Results from an investigation. Education Sciences & Society 14(1), 152-164 (2023).
28. Corsi, M., Rossi, P.G., Giannandrea, L., Winstone, N.: University didactics, innovation and inclusion. Assessment and feedback. Education Sciences & Society 14(1), 15-20 (2023).
29. Hattie, J., Gan., M.: Instruction based on feedback. In: Mayer, R.E., Alexander, P.A. (eds.) Handbook of research on learning and instruction, pp. 249-271. Routledge, New York (2011).
30. Ferguson, P.: Student perceptions of quality feedback in teacher education. Assessment & Evaluation in Higher Education 36(1), 51-62 (2011).
31. Weaver, M.R.: Do students value feedback? Student perceptions of tutors' written responses. Assessment & Evaluation in Higher Education 31(3), 379-394 (2006).
32. Ranieri, M., Rossi, P.G., Panciroli, C.: Active learning in large size classes. A multiple case study on technology-enhanced feedback in academic contexts. In: Gómez Chova, L., López Martínez, A., Candel Torres, I. (eds.) EDULEARN21 Proceedings, pp. 9154-9159. IATED Academy, Valencia (2021).
33. Osakwe, I., Chen, G., Whitelock-Wainwright, A., Gašević, D., Cavalcanti, A.P., & Mello, R.F.: Towards automated content analysis of educational feedback: A multi-language study. Computers and Education: Artificial Intelligence, 3, 100059 (2022).
34. Raffaghelli, J.E., Grion, V., de Rossi, M.: Data practices in quality evaluation and assessment: Two universities at a glance. Higher Education Quarterly 77(1), 7-26 (2021).
35. Chen, X., Xie, H., Zou, D., Hwang, G.J.: Application and theory gaps during the rise of artificial intelligence in education. Computers and Education: Artificial Intelligence 1, 100002 (2020).
36. Chen, L., Chen, P., Lin, Z.: Artificial intelligence in education: A review. Ieee Access 8, 75264-75278 (2020).
37. Salas-Pilco, S.Z., Yang, Y.: Artificial Intelligence Applications in Latin American Higher Education: A Systematic Review. International Journal of Educational Technology in Higher Education 19(1), 1-20 (2022).
38. Kochmar, E., Vu, D.D., Belfer, R., Gupta, V., Serban, I.V., Pineau, J.: Automated personalized feedback improves learning gains in an intelligent tutoring system. In: Bittencourt, I., Cukurova, M., Muldner, K., Luckin, R., Millán, E. (eds.) Artificial Intelligence in Education. 21st International Conference, AIED 2020 Proceedings, Part II, pp. 140-146. Springer, Cham (2020).
39. Zawacki-Richter, O., Marín, V.I., Bond, M., Gouverneur, F.: Systematic review of research on artificial intelligence applications in higher education–where are the educators?. International Journal of Educational Technology in Higher Education 16(1), 1-27 (2019).
40. Seidel, T., Stürmer, K.: Modeling and measuring the structure of professional vision in preservice teachers. American Educational Research Journal 51(4), 739-771 (2014).
41. Santagata, R., Angelici, G.: Studying the impact of the lesson analysis framework on preservice teachers' abilities to reflect on videos of classroom teaching. Journal of Teacher Education 61(4), 339-349 (2010).
42. van Es, E., Sherin, M.G.: Learning to notice: Scaffolding new teachers' interpretations of classroom interactions. Journal of Technology and Teacher Education 10(4), 571-596 (2002).
43. Star, J.R., Strickland, S.K.: Learning to observe: Using video to improve pre-service mathematics teachers' ability to notice. Journal of Mathematics Teacher Education 11(2), 107-125 (2008).

44. Seidel, T., Shavelson, R.J.: Teaching effectiveness research in the past decade: The role of theory and research design in disentangling meta-analysis results. Review of Educational Research 77(4), 454-499 (2007).
45. Sherin, M.G., van Es, E.: Effects of video club participation on teachers' professional vision. Journal of Teacher Education 60, 20-37 (2009).
46. Rossi P.G., Pentucci M.: Progettazione come azione simulata. Didattica dei processi e degli eco-sistemi. FrancoAngeli, Milano (2021).
47. Damiano, E.: La mediazione didattica. Per una teoria dell'insegnamento. FrancoAngeli, Milano (2013).
48. Altet, M.: L'apporto dell'analisi plurale dalle pratiche didattiche alla co-formazione degli insegnanti. In: Rivoltella P.C., Rossi, P.G. (eds.) L'agire didattico, pp. 329-348. La Scuola, Brescia (2017).
49. Kaufman, L., Rousseeuw, P.J.: Finding groups in data: an introduction to cluster analysis. John Wiley & Sons (2009).