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Research paper

Enhancement of academic programs and student guidance based on Generative AI (GenAI) and Student Evaluations of Teaching (SETs)

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ABSTRACT

In the field of higher education, teachers face a major challenge of meeting student expectations. On the other hand, students are not always able to judge the merits of the methods of the courses provided. Student evaluations of teaching (SETs) are a technique frequently used internationally to assess the quality of teaching provided. In return, these evaluations can be used for the continuous improvement of these lessons and therefore, raise the level of students learning. In this article, we propose to analyze the outputs of Student Evaluations of Teaching (SETs) by using techniques relating to Generative AI (GenAI) and more precisely the multidimensional data analysis in order to improve academic programs quality as well as academic guidance by assisting students in choosing options that best suits their needs, preferences and talents. This undeniably results in a reduction in university attrition rates.

1. Introduction

Nowadays, it is accepted that improving the quality of any human service depends on measuring the indicators relating to this service using instruments, and studying ways to improve it [1]. Even if passing judgment on the activity of a service is also a political act, which can be perceived by the professionals who exercise this service as a loss of autonomy [2]. In particular, in the field of higher education, teachers face a major challenge of meeting student expectations. On the other hand, students are not always able to judge the merits of the methods of the courses provided. [3, 4, 5, 6].

There are two main methods for assessing the quality of teaching. The first method consists of identifying certain quality indices collected in an observation grid by an external observer. While the second method is based on a questionnaire addressed to the recipients of the teaching in question [7]. This last possibility is frequently used once the learners are old enough to carry out relevant assessments. This is the case of the higher education sector in which such questionnaires are frequently used internationally to assess the quality of teaching provided. In return, these evaluations can be used for the continuous improvement of these lessons and therefore, raise the level of students learning. In this article, we propose to analyze the outputs of Student

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Evaluations of Teaching (SETs) by using techniques relating to Generative AI and more precisely the multidimensional data analysis in order to improve academic programs quality as well as academic guidance by assisting students in choosing options that best suits their needs, preferences and talents. This undeniably results in a reduction in university attrition rates.

2. Related works

Constantinou and Wijnen-Meijer [8] provide an overview of how Student Evaluations of Teaching (SETs) can be enhanced at the levels of instrumentation, administration and interpretation. Furthermore, this review explain that through the collection and triangulation of data from multiple sources, including students, peers, program administrators and self-awareness via the use of different methods such as peer reviews, focus groups and self-evaluations, it will be possible to develop a comprehensive evaluation system that will present an effective measure of teaching effectiveness, will support the faculty's career progression and will improve the quality of teaching in medical education.

Hornstein and Law [3] examine lliterature to support the contention that student evaluations of teaching (SETs) should not be used for summative evaluation of university faculty. Recommendations for alternatives to (SETs) are provided.

The scholarly debate over student evaluations of teaching (SETs) often focuses on whether (SETs) are valid, reliable, and unbiased. Esarey & Valdes [4] assume the most optimistic conditions for (SETs) stipulated by the empirical literature. Computer simulation reveals that using SETs to evaluate teachers can produce an unacceptably high error rate. This problem is due to the imprecision of the relationship between teacher quality and SETs, which exists even when they are moderately correlated.

Student evaluations of teaching (SETs) are heavily used by university administrators in decisions regarding faculty hiring, promotions, and merit salary increases. Stroebe [5] emphasizes that this approach biases the effective measurement of teaching, and contributes to the deterioration of its quality by causing grade inflation. Indeed, students tend to reward lenient instructors who require little work and to punish instructors who get strict grades. The study also shows that instructors want (and need) good SETs.

Student evaluations of teaching (SETs) are important for assessing university instructors' performance. However, Park & Cho [6] emphasize that this system seems biased as students' grade expectations result in rewards or penalties in SETs. The article explains that a change in expected grades due to factors other than lectures may alter students' attitudes toward SETs, and grade expectations may play a key role in reducing bias in SETs

The articles [9, 10] emphasize the importance of GenAI integration in higher education, highlighting both its potential benefits and concerns. Notably, there is a strong correlation between cultural dimensions and respondents' views on the benefits and concerns related to GenAI, including its potential as academic dishonesty and the need for ethical guidelines.

The authors argued that responsible use of GenAI tools can enhance learning processes, but addressing concerns may require robust policies that are responsive to cultural expectations.

3. Methods

To illustrate our proposals, we choose a case study concerning the university course « Mathematical and Computer Sciences » inherent to the Faculty of Sciences in Rabat. This course is based on a common core in the first two semesters S1 and S2, and offers 22 specialty programs distributed over the semesters S3, S4, S5 and S6 (see Table 1).

Table 1. Educational architecture of the course « Mathematical and Computer Sciences »

Semester	program code	program title
S3	M1	Programming I
	M2	Algorithmic II
	M3	Probability Statistics
	M4	WEB technology
	M5	Electronic
	M6	Operating system I
S4	M7	Operating system II
	M8	Programming II
	M9	Computer architecture
	M10	Data Structures
	M11	Numerical analysis
	M12	Electromagnetism
S5	M13	Database
	M14	Compilation
	M15	Operational research
	M16	Networks
	M17	Object Oriented Design UML
	M18	Object Oriented Programming JAVA
S6	M19	Databases and WEB programming
	M20	Human Machine Interface
	M21	Administration of computer networks
	M22	Network interconnection

To ensure a compromise between the consistency of the information and its readability, we will restrict our case study to 20 students pursuing their studies at the Bachelor's degree. Student Evaluations of Teaching (SETs) are carried out using a Likert scale ranging from 1 to 5 (1- Slightly satisfied, 2-Neutral, 3- satisfied, 4-Very satisfied, 5- Extremely satisfied). The simulation is performed using the software SPSS 23 (see fig. 1).

In recent years, higher education (HE) globally has witnessed extensive adoption of technology, particularly in teaching and research. The emergence of generative Artificial Intelligence (GenAI) further accelerates this trend. In this article, we propose to analyze the outputs of Student Evaluations of Teaching (SETs) by using techniques relating to Generative AI (GenAI) (see fig. 2) and more precisely the multidimensional data analysis in order to improve academic programs quality as well as academic guidance by assisting students in choosing options that best suits their needs, preferences and talents. This undeniably results in a reduction in university attrition rates.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22
E1	4	5	3	3	1	2	2	4	3	3	3	1	4	2	3	2	4	5	5	2	2	2
E2	2	3	1	3	5	4	4	2	4	1	1	3	2	4	1	5	2	2	1	2	5	4
E3	3	4	4	4	2	2	2	3	1	4	4	2	4	3	2	1	4	4	4	1	2	1
E4	4	4	3	5	2	1	2	5	1	2	1	2	3	1	2	2	4	4	3	2	1	1
E5	2	2	1	3	4	4	4	3	5	2	1	4	2	5	1	5	2	2	2	3	5	5
E6	5	4	3	4	2	2	1	5	2	4	3	1	4	2	4	2	4	5	5	2	2	1
E7	2	2	2	3	5	4	4	2	2	1	4	3	2	4	1	5	3	2	2	5	5	5
E8	5	5	2	3	1	1	1	5	1	5	3	1	5	2	4	2	5	5	5	2	2	1
E9	4	5	4	4	2	2	1	4	3	5	5	2	5	2	5	3	5	4	4	2	1	1
E10	2	3	1	2	5	5	5	3	4	2	1	4	2	4	1	5	3	3	3	4	5	5
E11	2	2	2	3	4	5	4	2	5	2	1	5	2	3	2	5	2	3	2	4	5	4
E12	5	5	4	4	2	1	1	5	2	4	4	1	5	2	4	2	5	5	5	2	2	2
E13	3	3	2	2	5	5	5	2	4	2	1	4	2	3	3	5	2	3	2	1	5	5
E14	4	4	5	4	3	2	2	4	2	5	5	4	4	2	5	2	5	5	4	1	2	1
E15	3	2	1	2	4	5	5	1	4	2	1	4	2	4	1	5	1	2	2	3	5	4
E16	1	2	1	2	4	5	5	2	4	1	1	4	3	4	2	5	2	3	2	4	5	4
E17	5	5	5	4	2	1	1	5	2	5	4	1	4	2	3	2	4	5	4	2	2	1
E18	4	4	5	4	2	2	2	5	1	5	5	2	4	2	5	2	5	4	4	2	2	1
E19	5	5	3	5	1	1	1	5	2	4	3	2	5	2	4	3	4	5	4	1	1	1
E20	2	2	1	2	5	5	5	2	4	1	1	4	2	5	1	5	2	2	3	2	5	5

Fig. 1. Ccorrespondence matrix between students and academic programs.

The proposed methods are based on the multidimensional data analysis and more precisely the Factor Analysis [Spearman, 1904] which is a collection of methods used to examine how underlying constructs influence the responses on several measured variables. There is a very wide range of fields of application for this method such as psychometrics, linguistics, geology, medicine, finance and peer-to-peer integration [11]. Examining the pattern of correlations (or covariances) between the observed measurements is the cornerstone of factor analysis. Metrics that are highly correlated (positively or negatively) are likely influenced by the same factors, while those that are relatively uncorrelated are likely influenced by different factors [Benzécri, 1973; Greenacre, 1984, 1993; Lebart, Morineau, and Warwick 1984]. Any method of factor analysis has for Input:

- a scatter plot $\mathrm{N}(I) = \{X_i \in R^P, i \in I\}$ the scatter plot $\mathrm{N}(I)$ in $\Re^3$ looks like a rugby ball. The vector X_i which represents the student Ei corresponds to the i-line of the correspondence matrix between students and academic programs.
- a weight assigned to point X_i
- a metric that calculates the similarity between points X_i (distance khi-deux)

For Output:

- Axes of inertia. The scatter plot has three orthogonal axes of inertia u_1, u_2, u_3 in $\Re^3$. The vector u_1 is the eigenvector (axe d'allongement maximal du nuage de points) corresponding to the largest eigenvalue of the matrix of inertia $V = X^t MX$ where X is the matrix of initial data centered by the centroid G, and M is the diagonal matrix of weight [12].
- Points X_i with their coordinates on the axes of inertia.
- Indicators for Decision-Making

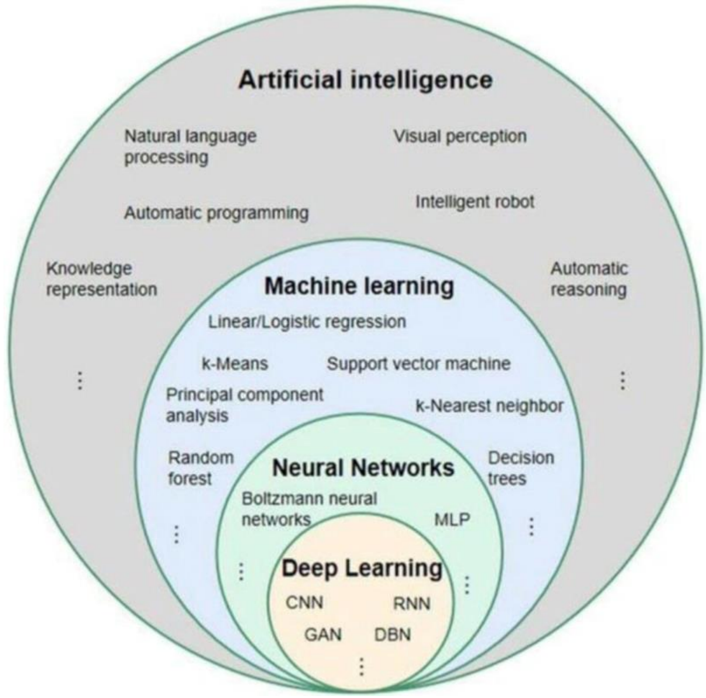

Fig. 2. Relationship between artificial intelligence, machine learning, deep learning, and neural network [Source: MLTut]

Factorial analysis consists of projecting the scatter plot $\mathrm{N}(I)=\left\{X_i \in R^P, i \in I\right\}$ onto the first factorial plane formed by the first two eigenvectors corresponding to the first two largest eigenvalues of the matrix of inertia $V = X^t MX$ (see fig. 3). The factor analysis of the correspondence matrix between academic programs and students is performed using the software SPSS 23

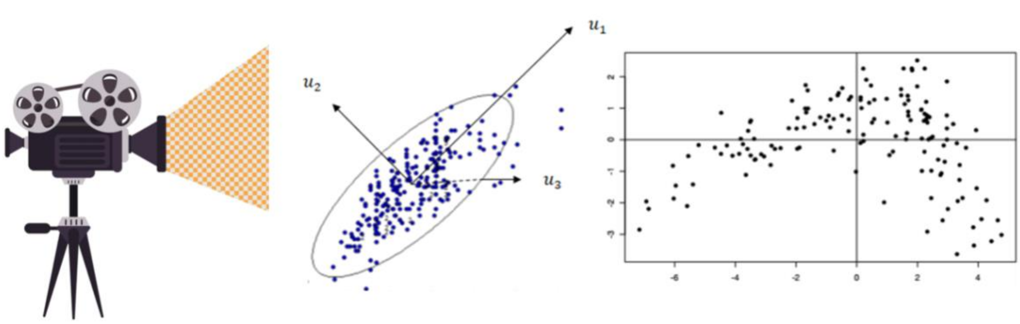

Fig. 3. Projection of scatter plot on the first factorial plane

4. Results

The eigenvalue histogram provides an efficient mechanism to evaluate the quality of the graphical representation. The quality of the graphics depends on the contribution of the sum of the first two eigenvalues to the total inertia. In our case, the quality is good since the first two eigenvalues account for 85,208% of the total variance $\frac{\lambda_1 + \lambda_2}{\sum_{\alpha=1}^{n} \lambda_\alpha}$ (see fig. 4)

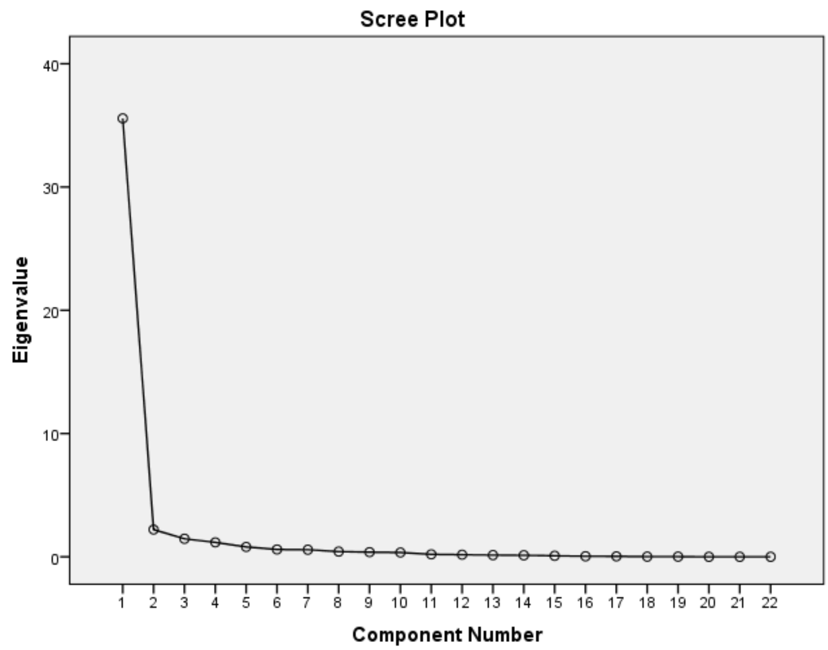

Fig. 4. Histogram of eigenvalues

The projection of the academic programs onto the first factorial plane formed by the first two eigenvectors corresponding to the first two eigenvalues of the direct analysis of the correspondence matrix between academic programs and students makes it possible to propose a new educational architecture for the master's cycle (see fig. 5). Indeed, we can detect the presence of two disjoint clusters which form the educational framework of two masters. On the one hand, a first Master entitled “Software Engineering” formed by the following programs: M1, M2, M3, M4, M8, M10, M11, M13, M15, M17, M18 and M19. On the other hand, a second master entitled “Systems and Networks” formed by the following programs: M5, M6, M7, M9, M12, M14, M16, M20, M21, M22 (see Table 2).

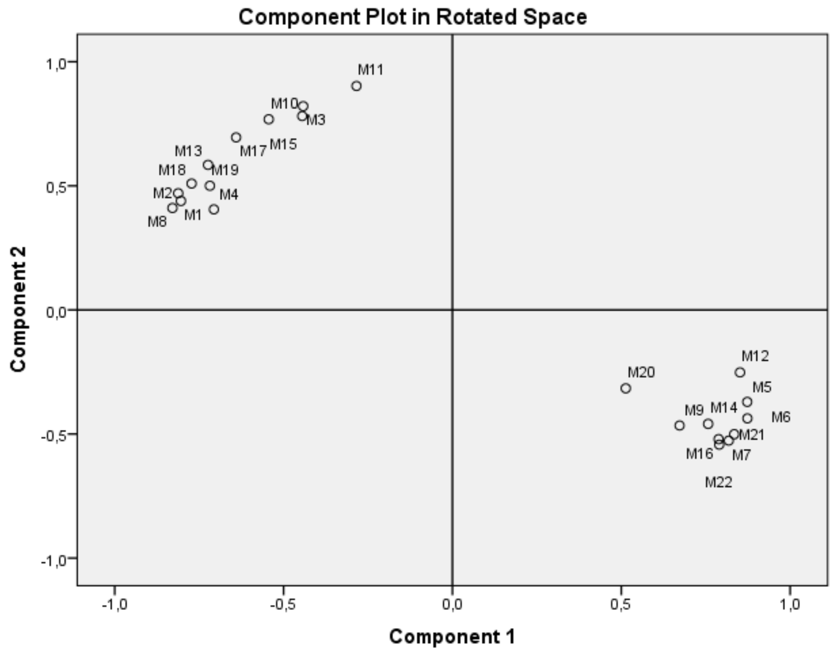

Fig. 5. Projection of direct cloud on the first factorial plane

Table 2. New educational architecture of the master cycle

Master	Academic programs
Software Engineering	M1, M2, M3, M4, M8, M10, M11, M13, M15, M17, M18 et M19.
Systems and Networks	M5, M6, M7, M9, M12, M14, M16, M20, M21, M22.

The projection of the students onto the first factorial plane formed by the first two eigenvectors corresponding to the first two eigenvalues of the dual analysis of the correspondence matrix between academic programs and students makes it possible to detect the preferred subjects of the students (see fig. 6). This makes it possible to improve the quality of academic guidance by assisting students in choosing options that best suits their needs, preferences and talents. This undeniably results in a reduction in university attrition rates. Therefore, students E1, E3, E4, E6, E8, E9, E12, E14, E17, E18 and E19 are strongly advised to continue their studies at the Master level "Software Engineering". While students E2, E5, E7, E10, E11, E13, E15, E16, E20 can profitably continue their studies at the "System and Networks" Master level (see Table 3).

Table 3. Academic guidance for students

Master	Students
Software Engineering	E1, E3, E4, E6, E8, E9, E12, E14, E17, E18 et E19
Systems and Networks	E2, E5, E7, E10, E11, E13, E15, E16, E20

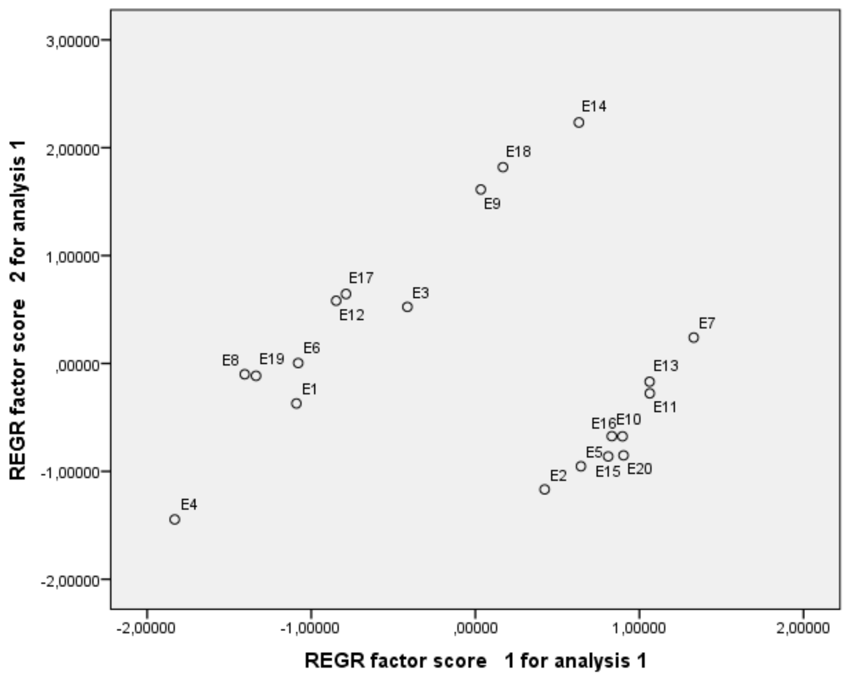

Fig. 6. Projection of dual cloud on the first factorial plane

To deal with the specific case of a student and offer him an optimal academic guidance which exactly matches his choices and preferences, we consider an n+1 row at the level of the correspondence matrix between academic programs and students (matrix size n*p, n students * p programs) in which we note the evaluations relating to this student for the different programs studied. The number Lij represents the evaluation of academic program j by student i according to the Likert scale previously described (see table 4).

The projection of the scatter plot relating to the dual analysis of the correspondence matrix between academic programs and students on the first factorial plane makes it possible to detect the affinity of this student in relation to the Masters courses offered. For example, it would be more judicious for the En+1 student to continue his studies at the level of the Master1 course entitled “Software Engineering” (see fig. 7).

Table 4. Insertion a new student into the correspondence matrix

	M1	**M2**	**.**	**Mj**	**.**	**Mp**
E1	L11	L12		L1j		L1p
E2	L21	L22	.	L2j	.	L2p
.	.	.	.	.	.	.
Ei	Li1	Li2	.	Lij	.	Lip
.	.		.	.	.	.
En	Ln1	Ln2	.	Lnj	.	Lnp
En+1	Ln+11	Ln+12	.	Ln+1j	.	Ln+1p

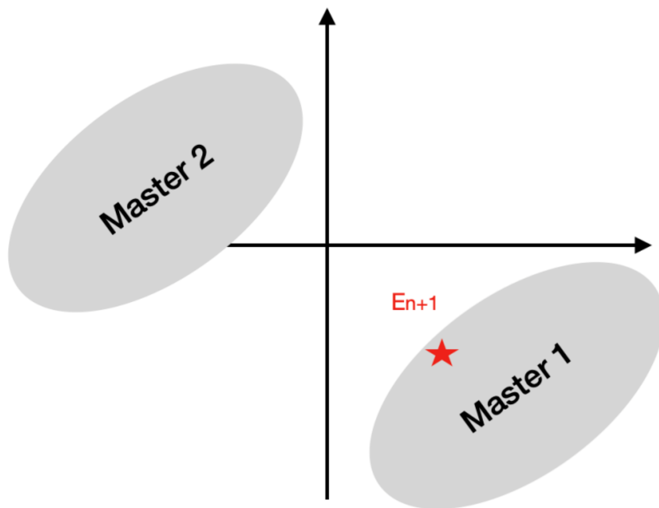

Fig. 7. Projection of a new student on the first factorial plane

5. Discussion et perspectives

In this article, the emphasis was placed on the use of Student Evaluations of Teaching (SETs) in order to improve academic guidance and choose an option that exactly matches student's profile. Another advantage of this approach would be the continuous improvement of the educational offer of the university establishment by detecting the presence of new, more attractive teaching sectors. Indeed, The projection of the academic programs onto the first factorial plane of the direct analysis of the correspondence matrix between academic programs and students makes it possible to propose a new educational architecture for the master's cycle. we can detect the presence of two disjoint clusters which form the educational framework of two masters : “Software Engineering” and “Systems and Networks”. This analysis can be used to support any new academic reform of the Master cycle.

Regulatory prescribing Student Evaluations of Teaching (SETs) in Moroccan universities is an imminent prospect of this work. Indeed, it would be wise to consider regulatory provisions to formalize, supervise and encourage this process of Student Evaluations of Teaching (SETs) and exploit its results by specialized units and development councils in an approach of continuous and retroactive improvement of the quality.

Another recommendation of this work would be formalize and automate the academic guidance for students through this process of (SETs) for the benefit of open access university establishments which contain an exorbitant number of students. This will make the task of providing academic guidance to students less expensive and tedious.

References

[1] A. S. Bryk, Accélerer la manière dont nous apprenons à améliorer. Éducation et Didactique, **11**(2), 11–30. doi:10.4000/educationdidactique.2796 (2017).

[2] S. Garcia & S. Montagne, Pour une sociologie critique des dispositifs d'évaluation. Actes de la Recherche en Sciences Sociales, **4**, 4–15 (2011).

[3] H . Hornstein, H. Law Student evaluations of teaching are an inadequate assessment tool for evaluating faculty performance. Cogent Educ.;**4**(1):1304016. (2017)

[4] J. Esarey & N. Valdes, Unbiased, reliable, and valid student evaluations can still be unfair, Assessment & Evaluation in Higher Education, 45:8, 1106-1120, DOI: 10.1080/02602938.2020.1724875 (2020)

[5] W. Stroebe, Student Evaluations of Teaching Encourages Poor Teaching and Contributes to Grade Inflation: A Theoretical and Empirical Analysis, Basic and Applied Social Psychology, 42:4, 276-294, DOI: 10.1080/01973533.2020.1756817 (2020)

[6] B. Park & J. Cho, How does grade inflation affect student evaluation of teaching?, Assessment & Evaluation in Higher Education, 48:5, 723-735, DOI: 10.1080/02602938.2022.2126429 (2023)

[7] P. Dessus, Évaluation de l'enseignement par les étudiants. Grenoble : Univ. Grenoble Alpes, Inspé, base de cours en sciences de l'éducation (2021)

[8] C. Constantinou, M. Wijnen-Meijer, Student evaluations of teaching and the development of a comprehensive measure of teaching effectiveness for medical schools. BMC Med Educ 22, 113 https://doi.org/10.1186/s12909-022-03148-6 (2022).

[9] A. Yusuf, N. Pervin, & M., Román-González, Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives. Int J Educ Technol High Educ 21, 21 https://doi.org/10.1186/s41239-024-00453-6 (2024).

[10] M. Abbas, , F. A. Jam, & T. I. Khan, Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. International Journal of Educational Technology in Higher Education, 21(1), 10. DOI: dx.doi.org/10.1186/s41239-024-00444-7 (2024).

[11] M. Ammari, , D. Chiadmi, , L. Benhlima, A Semantic Layer for a Peer-to-Peer Based on a Distributed Hash Table. In: Abd Manaf, A., Sahibuddin, S., Ahmad, R., Mohd Daud, S., El-Qawasmeh, E. (eds) Informatics Engineering and Information Science. ICIEIS 2011. Communications in Computer and Information Science, vol **254**. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-25483-3_9 (2011).

[12] J. Han, M. Kamber, & J. Pei, *Data Mining: Concepts and Techniques* Third Edition. Morgan Kaufmann (2012).

Conflicts Of Interest

The author declares no conflicts of interest.