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Teaching Tools for Enhancing Student Engagement in Higher Education

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Abstract

Objectives of the research: This project aims to identify the most effective tools for increasing student engagement.

Research methods: An ad hoc questionnaire to measure the engagement capacity of teaching tools, principal component analysis (PCA), and machine learning forward regression.

Structure of the article: Introduction, methodology and results (sampling, PCA, forward regression), discussion, and conclusions.

Research findings: Active interaction and modular organization promote student engagement. A student's inability to respond to questions about improving a subject often indicates a lack of interest. Engagement increases when previous teaching experiences have not incorporated interactive tools. Pre-class homework assignments enhance interest and make courses

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more practical. Tools that facilitate teacher-student interaction improve engagement, regardless of whether the teaching style is based on the teacher's practical experience or a student-centered approach.
Conclusions and recommendations: This research identifies several factors that significantly influence student engagement, including a modular structure, active classroom participation, pre- and post-class assignments, content quality, teaching style, and interaction through discussion platforms.

Keywords**:** higher education; learning approaches; statistical methods; student engagement; teaching tools; educational success.

Introduction

Academic studies have indicated that carefully selected teaching tools, such as educational technologies, instructional approaches, course organization, and teaching techniques play a crucial role in improving the overall effectiveness of educational delivery (Khalil & Ebner, 2013). Educational technologies can improve the quality of learning and promote collaboration and teamwork (Alonso et al., 2013). Educational success depends on how teachers and students adapt to learning needs (Bandura, 1977; Bruner, 1960; Freire, 1970; Piaget, 1970; Vygotsky, 1930). Each of these components has a unique learning style, so understanding their interaction is essential for effective education. The didactic unit represents a harmonious union between the subject matter expertise of the teacher and the specific needs of the students (Howe et al., 2019; Mortimer & Scott, 2003). This convergence of pedagogical skills and individual student characteristics is fundamental to effective teaching. Teachers can refine their methods by recognizing that each learner brings cognitive, emotional, and motivational qualities to the educational environment (Skinner, 2023; Skinner & Belmont, 1993).

The COVID-19 pandemic brought significant changes to education, accelerating the adoption of online teaching methods and educational technologies (Chiu, 2022; Mishra & Attri, 2020; Rijst et al., 2023). Studies have noted an increased reliance on platforms and videoconferencing,

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as universities provided tools to support online course delivery. However, research indicates that online teaching often results in reduced interaction and engagement (Bušljeta Kardum & Jurić Vukelić, 2021; Horta et al., 2022). The abrupt transition to online teaching prompted by the pandemic has raised questions about the effectiveness of traditional teaching tools compared to new technological ones. This shift has ushered in challenges for educators and students, such as the isolation inherent in online learning, where student participation has become even more crucial (Deng et al., 2020; Mustafa et al., 2022; Ramoshaba & Kgarose, 2022).

Course structure also affects student engagement. A well-designed course must be clear and coherent and communicate learning objectives effectively, while prioritizing active learning and student-centered methods that foster problem-solving skills. Such an approach enhances student participation and encourages the development of critical thinking (Barr & Tagg, 1995). Given these considerations, it is crucial to conduct a thorough analysis to determine the most effective tools for increasing student participation within the teaching unit. Moreover, it is vital for educators to continually evolve, and equip themselves with the skills necessary for professional competence in an increasingly cross-cultural and technologically integrated Western educational system. This study aims to identify strategies and tool that most effectively foster student engagement in teaching environments. The methodology, results, and analysis are presented in the following sections.

Methodology

This exploratory study seeks to identify relationships between variables that enhance students' commitment to a subject. It is a descriptive validity study that does not aim to infer outcomes based on binary variables and employs an orthogonal design for the analysis of closed-ended questions. We incorporate variables that can be considered linearly independent of the principal components to better understand the survey results, effectively reducing the dimensionality of the data.

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Population and Sample

The study sample consists of 145 university students enrolled in Statistics and Management courses during the 2021–2022 academic year. Of these, 55 students were based in Spain (at URJC), 75 in the United States (at WashU and UST), and 15 in France (at UCO). Initially conducted as primarily online courses, the activities transitioned to a blended learning format (Caner, 2012; Lightner & Lightner-Laws, 2016).

These courses attracted a diverse group of students from around the globe: 35.2% were from Spain, 25.5% from the United States, 10.3% from France, 5.5% from China, 4.8% from India, and the remaining participants hailed from other countries. The majority of participants (73.8%) were pursuing bachelor's degrees, while the rest were enrolled in master's programs or other professional degrees. In addition, 86.9% of the participants were under the age of 29. Midway through the semester, an online survey was conducted. The questionnaire was administered in English as the international scope of the study. In this article, the variables are labeled in English in the tables and graphs, while the factors are presented in Spanish as they emerged from the data analysis.

The questionnaire aimed to identify factors influencing student participation, encompassing both variables recognized in previous literature and new variables. The survey was divided into two parts: the first consisted of closed-ended "yes" or "no" questions. A response of "0" indicated that the topic was irrelevant to improving student participation, while a response of "1" indicated relevance. The second part featured open-ended questions that allowed students to describe actions that had supported their learning or suggest ways to improve teaching. The responses to the open-ended questions were subsequently converted into binary data for analysis.

It is important to note that the categories derived from the open-ended responses cannot be directly applied to linear correlations or predictions due to the absence of predefined response options. However, statistically significant characteristics associated with the "1" category are expected to have an impact on the student population. If respondents

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had been given more predefined response options, it is likely that there would have been more positive responses, potentially resulting in stronger correlations with the binary variables coded from the open-ended responses.

As such, the Principal Component Analysis (PCA) focuses on the first set of closed-ended questions. These questions are grouped into three categories related to teaching: "Teaching Method (MT)," "Teaching Style (ST)," and "Course Structure (CS)." Additionally, a separate category, "Most Engaging (MA)" is included to compare aspects of the course that were successful with other student experiences that did not contribute to educational engagement. The binary characteristics extracted from the open-ended questions are divided into two distinct categories: "Open-ended questions about the attractiveness of the learning experience (OLA)" and "Open-ended questions about opportunities to improve the learning experience (OOI)." These categories reflect both positive aspects of the learning process and areas for potential improvement to increase student engagement.

Principal Component Analysis (PCA)

PCA is an essential statistical technique for uncovering hidden structures in complex datasets. It simplifies and reduces the dimensionality of correlated variables by transforming them into uncorrelated principal components. PCA identifies variables that capture the greatest variability in the data, under the assumption that the original variables can be linearly combined into new independent components. Principal component analysis for binary variables (PCAB) is commonly employed in machine learning and biology, particularly for analyzing genomic structures (Song et al., 2019). While logistic transformations for categorical variables are often used, we opted for linear PCAB due to the binary nature of our variables, following methodologies used in studies that link hard-to-measure ordinal variables with easier-to-measure binary ones (Bollen et al., 2002; McKenzie, 2005).

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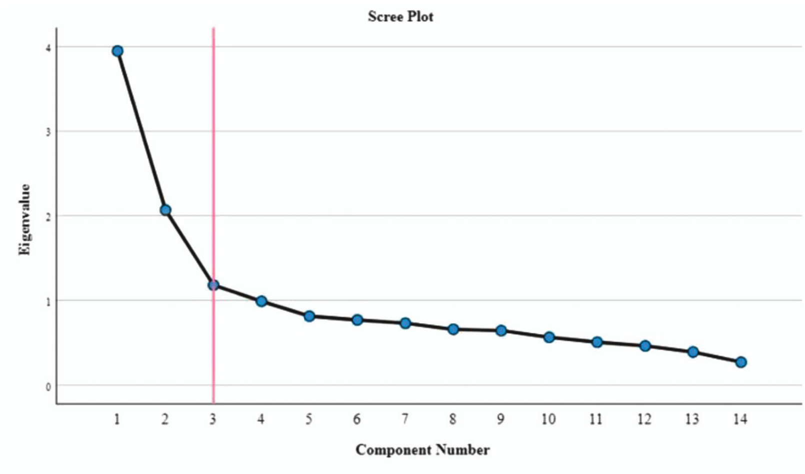
Kolenikov and Angeles (2009) examined the advantages and limitations of this methodology. Linear PCAB has been effectively used in World Bank studies on the socioeconomic status of citizens in emerging countries (Filmer & Pritchett, 2001; Vyas & Kumaranayake, 2006). Its effectiveness stems from the challenges of measuring ordinal variables while leveraging the simplicity and accessibility of binary indicators, such as household appliance ownership and access to basic services, which serve as benchmarks for well-being.

We will use the component scores to perform a machine learning model via stepwise forward linear regression. The PCA is then analyzed as a factor analysis by applying the principle of interpretability (Arabie, 1991). The decision on how many components to retain depends on the data and the objectives of the study (Costello & Osborne, 2005; Jolliffe, 1986). This decision is iterative and relies on multiple criteria as well as expertise (Tabachnick & Fidell, 2013; Watkins, 2018). Common criteria for assessing the feasibility of PCA include the determinant value of the correlation matrix, the Kaiser-Meyer-Olkin index (KMO) (Kaiser, 1970), and Bartlett's test of sphericity (Fabrigar et al., 1999; Kaiser, 1974; Stevens, 1996).The model is validated using three components, based on the following statistics and tests:

1. The determinant of the correlation matrix is close to zero (0.026).
2. Kaiser's criterion (Kaiser, 1970; Yeomans & Golder, 1982): the eigenvalues are greater than one.
3. Cattel's criterion (Cattell, 1965; Horn, 1965): the number of components is selected where the downward trend in the scree plot levels off (Figure 1).
4. The total variance explained by the three components is 51.4%, which does not meet the general rule of 60%. However, including a fourth component compromises interpretability.
5. Bartlett's test (Bartlett, 1950) confirms that the null hypothesis—that the correlation matrix is equal to the identity matrix in the population—is rejected.

Figure 1. Scree plot and Cattell's rule



From the analysis of the rotated component loadings matrix, we present only the tables of factor saturations (maximum loadings) that serve to name the component and identify the factor.

In Table 1, we observe that the first component is associated with teaching style (TS) variables. These variables share a common characteristic: the teacher bases instruction on their professional experience and actively interacts with students to address concrete and practical situations. Accordingly, we identify the component as "F1: Teaching Style Based on the Teacher's Practical Experience."

Table 1. Factor Saturations of the First Component (PC1)

Variable	Loading
ST7. The professor uses real-life examples to vividly illustrate the theoretical framework	0.685
ST4. The professor is passionate about the subject they are teaching	0.656
ST3. Clear expectations and detailed instructions are provided by the professor	0.653
ST5. The professor encourages debate among the students	0.644
ST1. The professor is accessible and available to students	0.636
ST6. The professor creates opportunities for competitions among students to generate ideas	0.624

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In Table 2, we observe a mix of style variables (ST) and variables from the group "More Attractive than Other Teaching Experiences" (MA). The variable with the highest saturation is ST2, which refers to the teacher's ability to clarify course objectives and instructions. Notably, the variables in the MA group provide reasons why the teacher's classes are preferred over those of others. Therefore, the positive saturation in MA6 and MA1 should have their signs reversed since they favor the reference teacher. These variables relate to the teacher's professionalism, including their organization of the subject, promptness in answering questions, and use of practical exercises with a more formal and traditional approach. We identify this component as "F2: Traditional Teacher-Centered Teaching Style."

Table 2. Factor Saturations of PC2

Variable	Loading
ST2. The professor clearly states the instructions and objectives of the course	0.851
MA6. The professor takes a long time to respond to questions	0.716
ST8. Students frequently do different assignments to demonstrate they can apply what they have learned in class	0.695
MA1. The e-learning platform content is poorly organized	0.664

In Table 3, all the saturating variables belong to the "More Attractive (MA)" group, which makes them inherently comparative with other teaching experiences. The predominant characteristics highlight interaction and feedback between students and teachers. We can observe that the variable with the highest saturation is MA7 (feedback on post-class questionnaires). These variables correspond to the concept of the "Student-Centered Classroom" (Büchele, 2021; Jones, 2007), which emphasizes the teacher's role as an active participant in communication with students. Accordingly, we designate this component as "F3. Student-Centered Teaching Style."

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Table 3. Factor Saturations of PC3

Variable	Loading
MA7. The professor does not use polls to ask questions in class	0.799
MA5. The professor is not always available	0.698
MA9. The professor's style is more lecturing than interactive; they focus less on asking questions to capture the students' interest	0.544
MA3. Students do not interact one-on-one with other students	0.498

Forward Regression on Dummy Variables

Stepwise forward regression is a machine learning variable selection technique used to determine which independent variables best explain the variability in a dependent variable. When the dependent variable is binary, this technique can also help identify the most significant predictors (Hosmer Jr et al., 2013). Our study sought to identify connections rather than predict the probability of the dependent variable. By conducting a thorough analysis of forward regression models for each characteristic, we found that the statistical relationships revealed by the model do not necessarily match theoretical expectations. Nevertheless, they offer valuable insights into the influences among variables.

As potential independent variables, we selected the principal components along with questions that were not included in those components. Standardized coefficients are useful in assessing the relative importance of the independent variables within the regression. These coefficients are derived by dividing the regression coefficient of each variable by its standard deviation, which enables direct comparisons (Hair et al., 2010). We conducted a machine learning analysis using this methodology across all variables. The most relevant models are presented below.

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Table 4. Influential Variables (R^2 = 0.266) in "Reading and Viewing Prior to the Class" (MT1)

Variable	Standardized Coefficients	Sig.
CS2. The modular organization of the course enhances engagement	0.302	0
MA10. The course expectations are unclear	0.21	0.01
OOI5. Increased practice opportunities	0.18	0.02
MT4. Use of discussion boards and feedback	0.177	0.03
CS5. The e-learning platform materials are appealing	0.156	0.04

Pre-class homework assignments (MT1) are strongly influenced by the effective organization of the course into modules (CS2). These assignments are perceived as more attractive than other courses where expectations were unclear (MA10). In addition, they enhance student interest by incorporating practical elements into the coursework (OOI5) and using discussion boards and feedback platforms (MT4).

Table 5. Influential Variables (R^2 = 0.594) in "Out-of-Class Video" (MT2)

Variable	Standardized Coefficients	Sig.
MA15. Teacher's reluctance to embrace change	0.406	0
OLA6. Dedication /Commitment	0.227	0.001
OLA21. Proficiency in language skills	0.19	0.007
OLA9. Mastery of course content and subject area	0.197	0.006
OLA12. Quality of course materials (e.g., PowerPoint presentations, videos, etc.)	0.16	0.024

The use of recorded teaching videos as supplementary material to classes (MT2) is positively associated with the teacher's professional dedication and commitment (OLA6), their ability to convey content in multiple languages (OLA21), and the quality of course materials such as PowerPoint presentations and videos (OLA12). These factors significantly enhance student engagement. Furthermore, such content gains appreciation in comparison to previous experiences where these resources were unavailable (MA15).

Table 6. Influential Variables (R^2 = 0.594) in "Post-Class Diary Assignments" (MT3)

Variable	Standardized Coefficients	Sig.
OLA22. Lack of engagement ("Nothing")	-0.307	0
F1. Teaching style based on the practical experience of the teacher	0.142	0.073
MA2. The professor does not show passion for the subject they are teaching	0.211	0.006
OLA2. Dynamic class activities and interactions	-0.179	0.017
MT4. Use of discussion boards and feedback	0.158	0.042

Engagement stemming from daily post-class diary assignments (MT3) is inversely proportional to students perceiving the subject as uninteresting (OLA22). However, it positively correlates with the perception of the teacher's motivation and enthusiasm for the subject (MA2). These assignments also heighten interest in dynamic and interactive activities (OLA2) and are enhanced when paired with discussion boards and feedback (MT4).

Table 7. Table 7. Influential Variables (R^2 = 0.319) in "Discussion Boards and Feedback" (MT4)

Variable	Standardized Coefficients	Sig.
CS2. Modular course organization enhances engagement	0.161	0.042
CS4. Constant student interaction makes this class highly engaging	0.201	0.008
F2. Traditional teacher-centered teaching style	-0.188	0.011
MT1. Pre-class reading and viewing assignments	0.211	0.007
OLA12. Course material (PowerPoint, videos, etc.)	-0.148	0.042
OOI10. Increased student participation	0.16	0.028
MT3. Post-class diary assignments	0.153	0.038

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Student engagement through discussion boards and feedback platforms (MT4) increases when the course is organized into clear modules (CS2) and when activities encourage continuous student interaction (CS4). Pre-class assignments (MT1) and post-class diary activities (MT3) further enhance engagement. Discussion platforms also highlight areas where course materials (OLA12) may lack appeal, and thus encourage greater student participation (OOI10).

Table 8. Influential Variables ($R^2 = 0.372$) in "The Modular Organization of the Course Helps You Engage" (CS2)

Variable	Standardized Coefficients	Sig.
F1. Teaching style based on the teacher's practical experience	0.317	0
MT1. Pre-class reading and viewing assignments	0.335	0
OOI5. Increased emphasis on practice	-0.174	0.012
OLA17. Appropriate time for assimilating knowledge	0.196	0.004
OLA16. Emphasis on practice over theory	0.163	0.019

Student engagement attributed to the modular organization of the course (CS2) is positively influenced by pre-class assignments (MT1), the provision of adequate time for knowledge assimilation (OLA17), and a focus on practical rather than theoretical learning (OLA16). However, the modular structure also highlights an alternative aspect, as student interest in making the course more practical (OOI5) shows a slight negative correlation.

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Table 9. Influential Variables (R^2 = 0.477) in "Video Conference with Student Interaction" (CS3)

Variable	Standardized Coefficients	Sig.
(Intercept)		0
F1. Teaching style based on the practical experience of the teacher	0.501	0
F3. Student-centered teaching style	0.298	0
F2. Traditional teacher-centered style	-0.251	0
OOI9. Language proficiency	0.218	0.001
OLA18. Interest in the subject	-0.173	0.007
OOI5. Increased practice	-0.164	0.013

Video conferences with interaction (CS3) enhance student engagement by incorporating teaching styles based on the teacher's practical experience (F1) and a student-centered approach (F3). They are also an alternative to the traditional, lecture-based teaching style (F2). This format boosts student interest by offering opportunities to learn languages (OOI9). However, if the subject matter is inherently engaging (OLA18) or there is a greater demand for practical activities (OOI5), the relative impact of videoconferencing on interaction and engagement may diminish.

Table 10. Influential Variables (R^2 = 0.21) in "Students' Interaction Constantly Makes This Class Very Engaging" (CS4)

Variable	Standardized Coefficients	Sig.
F1. Teaching style based on the teacher's practical experience	0.319	0
MT4. Use of discussion boards and feedback	0.227	0.004
CS5. Attractiveness of e-learning platform materials	-0.214	0.007

Student engagement attributed to constant interaction (CS4) improves when the teaching style emphasizes practical experience (F1) and

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incorporates the use of discussion boards (MT4). Interestingly, this engagement is inversely related to the attractiveness of e-learning materials (CS5).

Table 11. Influential Variables (R^2 = 0.234) in "Nothing to Improve in the Course" (OLA22)

Variable	Standardized Coefficients	Sig.
MT3. Post-class diary assignments	-0.295	0
OOI5. Increased focus on practical exercises	-0.226	0.003
F2. Traditional teaching style	0.204	0.008
OOI0. Additional time allocation	-0.162	0.034
OOI2. Improving teaching materials/Syllabus preparation	-0.155	0.04

When students indicate that there is "nothing to improve" in a course (OLA22), this is often synonymous with a lack of engagement. Reduced post-class assignments (MT3), limited practice opportunities (OOI5), insufficient time allocation (OOI0), and poorly prepared teaching materials or syllabus (OOI2) are factors associated with this lack of commitment. However, the traditional teaching style (F2) emerges as the only positive influence on engagement when students perceive no room for improvement.

Table 12. Influential Variables (R^2 = 0.306) in "Fun Classes/Comfort" (OLA3)

Variable	Standardized Coefficients	Sig.
OLA5. Passion/Vocation	0.343	0
MT4. Use of discussion boards and feedback	0.2	0.007
OLA2. Dynamic / Interactions	0.198	0.008
F2. Traditional teaching style	-0.199	0.008
OLA7. Closeness/Accessibility/Availability	0.155	0.03

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Student engagement increases significantly when classes are perceived as enjoyable and comfortable (OLA3). This is strongly associated with the passion and dedication exhibited by the teacher (OLA5), their approachability and availability to students (OLA7), the dynamic and interactive nature of the lessons (OLA2), and the inclusion of discussion boards and feedback platforms (MT4). However, this positive engagement appears inversely related to the traditional teaching style (F2), which suggests that a more traditional approach may detract from the perceived jovial and engaging atmosphere of the classes.

Discussion

The extraction of principal components from dummy variables is presented as a robust tool for reducing the dimensionality of binary variables that exhibit specific characteristics described in the methodology section. Including binary categories derived from open-ended questions, while not generalizable to the population, can help discover relationships that may not have been previously explored in the literature. Future research should propose theoretical models for confirmatory analysis to better understand the relationships uncovered in this study.

Machine learning models used in this study do not imply theoretical or causal relationships but instead reveal existing correlations among variable groups. In some cases, theoretical relationships may be inferred by reorganizing the terms; in others, simultaneous relationships emerge that encourage the proposal of partial models for further investigation. The coefficients of determination offer an indication of the variance explained by the linear machine learning model. A low value for this coefficient suggests either an absence of predictive variables or the existence of interdependence among the variables included in the model.

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Conclusions

Principal component reduction reveals that fundamental teaching qualities are linked to different teaching styles, which are not mutually exclusive. A teacher may adopt several of these styles to varying degrees. The identification of these components as underlying characteristics highlights the importance of teaching styles in meeting the specific needs of each teaching unit, encompassing students, teachers, and subject matter.

Although the playful aspect of classes was not initially regarded as a tool to enhance student engagement, the automated analysis in Table 12 shows its significance. Recent studies have demonstrated that incorporating fun elements and playful activities into higher education can substantially boost student engagement (Anandarajan & Simmers, 2017; Heimbuch & Lubbe, 2020; Yang et al., 2020).

Conclusions Drawn from the Machine Learning Model

1. Pre-class Homework Assignments and Modular Organization:
   Pre-class homework assignments (MT1) are strongly linked to the effective modular organization of courses (CS2). This structured format appeals to students and increases their interest in making the course more practical (OOI5). In addition, these assignments encourage greater interaction through discussion and feedback platforms (MT4).
2. Parallel Recording of Teaching Videos:
   Recording teaching videos parallel to lectures (MT2) is associated with the teacher's ability to effectively deliver content, overcome language barriers, and provide high-quality presentations. Students report higher levels of engagement and participation compared to previous experiences without such content (MA15).
3. Daily Post-Class Assignments and Student Engagement:
   While daily post-class assignments (MT3) are inversely related to student interest in the subject (OLA22), they enhance students' perceptions of teacher motivation (MA2). Additionally, these assignments foster an increased interest in dynamic and interactive activities (OLA2).

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4. Feedback Discussion Platforms:
   Feedback discussion platforms (MT4) increase student engagement when combined with modular course organization (CS2) and interactive activities (CS4). These platforms also complement pre- (MT1) and post-class assignments (MT2). Additionally, they serve as alternatives to the general attractiveness of course materials (OLA12) and incentivize more interaction (OOI10).
5. Module Organization and Student Engagement:
   Well-organized course modules (MT2) are positively correlated with pre-class assignments (MT1), sufficient time for knowledge assimilation (OLA17), and a practical rather than theoretical approach (OLA16). This organization shows an alternative dimension of student interest in making the subject more hands-on and practical (OOI5).
6. Interactive Videoconferences and Teaching Styles:
   Interactive videoconferences (CS3) enhance student engagement, particularly when employing teaching styles based on the teacher's practical experience (F1) and a student-centered approach (F3). These videoconferences serve as alternatives to traditional teaching styles centered on classical teacher performance (F2). Moreover, they boost student interest by integrating language-learning opportunities (OOI9).
7. Teaching Style and Student Engagement:
   Student engagement is positively influenced by teaching styles that convey passion, accessibility, and dynamism in the classroom (OLA3, OLA5, OLA7, OLA2). The use of discussion platforms (MT4) further supports this engagement. Classes characterized by a jovial and comfortable atmosphere also serve as alternatives to traditional, performance-based teaching styles (F2).
8. Indicators of Lack of Student Engagement:
   When students fail to identify areas for improvement in the subject (OLA22), this may indicate a lack of engagement. In such cases, engagement is positively related to traditional teacher-centered teaching styles (F2) but is inversely related to frequent post-class assignments (MT3), excessive practice (OOI5), insufficient time (OOI0), and inadequate development of teaching materials (OOI2).

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In summary, student engagement is shaped primarily by teaching styles and specific factors such as course module organization, in-class interaction, pre- and post-class assignments, content quality, and discussion platforms. These elements may interact in alternative, complementary, or substitutive ways, depending on their interplay and individual student preferences.

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