# Multidimensional Factors Influencing Student Absenteeism in Higher Education: An Empirical Study using Exploratory Factor Analysis and Logistic Regression

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*Abstract:* - Student absenteeism is a complex systemic problem, often described in the literature as a multifactorial phenomenon, which is not only related to the lack of interest of the student, but also to the educational environment. This article analyzes these determinants using data from responses collected from undergraduate students (N = 63). The ten items of the questionnaire that reflect the perceived motives of the students for absenteeism were analyzed through the Exploratory Factorial Analysis. This analysis evidenced a solid three-factor organization that reveals instructional references, personal and motivational determinants, and logistical constraints. These unknown dimensions were later included in a binary logistic regression model that estimates the likelihood of repeated absenteeism. The results indicate that stronger intrinsic motivation and positive perceptions of the quality of training significantly reduce the likelihood of repeated absenteeism, while logistical barriers and work-related commitments substantially increase it. Other factors, including extrinsic motivation and personal hardship, did not show statistically significant effects. The results highlight the complex nature of absenteeism and highlight the imposition of introduced pedagogical and institutional strategies addressing both motivational processes and structural limitations. The article uses practical examples from an underfunded university environment to show how students from socioeconomic backgrounds can be motivated to participate more actively.

*Key-Words:* - Student Absenteeism, Higher education, Motivational factors, Quality of training, Structural barriers, Exploratory factorial analysis, Logistic regression

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## 1 Introduction

University absenteeism is a major challenge for academic management, having a direct impact on student success and dropout rate. This problem compromises not only individual results, but also the efficiency of the teaching process, affecting the quality standards of the entire university. Participation in the teaching activities is conditioned by a mix of interdependent factors: from self-discipline and personal motivation, to issues related to educational management, such as course organization and the quality of resources made available, [1], [2], [3], [4]. At the same time, constant participation in the educational process is conditioned by the pressure of external factors, in particular professional responsibilities and family obligations, which may restrict the availability of students, [5].

Unlike the highly studied Western systems, universities in Central and Eastern Europe remain under-explored in absenteeism. Given the socio-economic and post-pandemic context specific to the region, the analysis of these local dynamics is crucial for the development of tailored and effective educational strategies.

This study complements the literature by examining the causes and correlations of absenteeism at a public university in Romania, at the undergraduate level. The research aims to achieve three main objectives:

1 Analysis of the interdependence between psychological mechanisms of self-regulation (motivation) and contextual barriers of the university environment (structure), to determine the absenteeism of students.

2. Integrating these dimensions into a regression-based predictive model.

3. Highlighting the methodological implications of combining factor-analytic techniques with regression modelling in the study of complex educational behaviours.

The study employs a two-step analytical approach to achieve these goals.

Exploratory Factorial Analysis (EFA) is first used to identify dormant constructs underlying perceived barriers and motivational guidelines. A binary logistic regression model is then applied to estimate the likelihood of repeated absenteeism using extracted latent factors along with selected demographic characteristics. This integrated strategy provides a nuanced perspective on how psychological influences and contextual conditions together shape attendance behavior in higher education environments.

Taking into account previous research that analyzes student participation in universities in Romania, [6], this article advances the discussion by applying unnoticed variable techniques together with logistic regression to identify motivational, instructional, and structural determinants associated with recurrent absenteeism.

# 2 Review of the Literature

Student absenteeism is seen as a significant challenge in higher education, consistently in close correlation with lower academic performance, increased risk of dropping out of school, and broader patterns of social inequality. Early research has established a strong positive association between course attendance and academic success, [7], while more recent studies suggest that the post-COVID context has intensified activities/actions, with increasing levels of chronic absenteeism and increasing structural differences, [8]. Research also indicates that absenteeism disproportionately affects students from socio-economically disadvantaged backgrounds, often reflecting reduced duty, weaker academic belonging, and increased psychosocial stress, [9].

Systematic conclusions further show that learning environments that support student autonomy tend to mitigate absenteeism, while rigid curricular structures and limited opportunities for student action may intensify it, [10]. Classrooms that fail to meet the basic psychological needs of students for autonomy, competence, and networking are particularly vulnerable to detachment, [11]. Instructional quality represents another key determinant of attendance behaviour. Student‑centred pedagogies - characterized by clarity, constructive feedback, and curricular relevance - are associated with improved attendance, especially among students with limited resources, [12]. Inclusive instructional approaches that foster trust, collaboration, and perceived relevance further support equitable participation. Additional studies highlight the benefits of self-directed learning and well-designed blended courses, where learning strategies mediate satisfaction and engagement, [13].

At the institutional level, official data point to strong links between absenteeism, dropout risk, and the efficient use of educational resources, [14]. Existing research supports a multidimensional perspective on absenteeism that integrates:

(i) psychological, social, and contextual components to explain why students miss classes;

(ii) institutional influences, including program flexibility and instructional quality; and

(iii) contextual pressures, arising from socioeconomic constraints and post-pandemic disruptions.

Evidence from Romanian higher-education contexts suggests that interactive teaching‑learning‑evaluation methods contribute to stronger student engagement and enhanced perceptions of instructional relevance, [15]. Despite these contributions, most empirical evidence still originates from Western higher-education systems. There remains a comparatively limited understanding of how these determinants operate within Central and Eastern European contexts, and only a small number of studies employ multivariate statistical approaches to quantify their effects.

The main reason for absenteeism among Romanian undergraduate students is identified through Exploratory Factor Analysis (EFA) and binary logistic regression in this research. The understanding of the interaction of motivational, instructional, and structural factors that shape presence behavior in a regional context that is still underrepresented in international literature is more refined through this approach.

# 3 Theoretical framework

## 3.1 Academic Justification

The analysis of the presence and involvement of students in higher education environments relies heavily on justification. Within the Theory of Self-determination, intrinsic motivation - established in curiosity, personal interest, and the desire to master knowledge - supports sustained academic engagement, while extrinsic motivation, driven by external notes or constraints, tends to encourage compliance with short-term responsibilities rather than long-term participation, [16]. When students attend classes because they find the learning meaningful, they are more likely to persist even when faced with challenges.

Absenteeism can therefore reflect not only behavioural disengagement but also students' perceptions of limited autonomy or instructional irrelevance, [17]. Classical models of academic perseverance similarly emphasize the importance of integration, self-regulation, and internalized commitment in shaping participation, [18], [19].

A constant presence is more likely to be maintained by students who feel connected to their academic environment, confident in their skills, and supported in their learning. Students with low independence or a weak academic background can distance themselves more easily.

### 3.2 Participation and Engagement

Student engagement quality is crucial for determining the impact of attendance on courses, even though it is strongly linked to academic performance. Skipping courses, seminars, and laboratories that students believe are unproductive or insufficiently interactive may indicate dissatisfaction with teaching practices or a preference for more autonomous learning formats. In this analytical framework, the phenomenon of absenteeism can be interpreted as an indirect indicator of the quality of the educational process, emphasizing the need to adopt student-centered pedagogical models. Such approaches aim at activating cognitive engagement by facilitating learning experiences with a high degree of personal and professional relevance. Strengthening autonomy and interactivity in curricular configuration increases the likelihood that students will become aware of academic presence as a fundamental vector of their own development.

### 3.3 Educational Efficiency and Consequences of Absence

Absenteeism undermines the efficiency of the educational process, affecting both the student's course and the performance of the institution. By not attending courses, students lose access to essential interactions, immediate feedback, and the logical flow of cumulative learning, which limits their academic development and the acquisition of key competences. These gaps are becoming increasingly difficult to recover from in disciplines where concepts are progressively structured, turning sporadic absences into a major obstacle to long-term success.

At the institutional level, persistent absenteeism undermines the efficient use of educational resources and challenges accountability structures, especially in systems with limited instructional capacity. High rates of absence can strain teaching effectiveness, distort workload planning, and diminish the overall return on investment in instructional provision. Consequently, many policy frameworks incorporate attendance monitoring into broader strategies aimed at improving equity, inclusion, and academic success, [20].

### 3.4 Contextual and Structural Factors

Beyond motivational and pedagogical factors, absenteeism is influenced by a complex socioeconomic and institutional context. Financial constraints that require employment, household, or care responsibilities, together with the rigidity of the educational system, significantly increase the risk that students will be absent. In Central and Eastern Europe, structural constraints - including rigid timetables, underdeveloped infrastructure, and limited access to student-support services - further intensify these challenges, [21], [22]. Post-pandemic disruptions have also highlighted persistent inequalities in digital access, academic belonging, and motivational stability, all of which contribute to uneven patterns of participation.

Summary. This framework identifies four complementary dimensions - motivation, engagement, efficiency, and structural context - that jointly influence absenteeism. These factors guide the empirical strategy of this study, namely, exploratory factorial analysis is used to identify the implicit motivational and institutional dimensions, while binary logistic regression quantifies their effects on repeated absenteeism.

Together, these approaches provide a coherent basis for understanding how psychological and contextual factors interact to shape the conduct of presence in higher education environments.

## 4 Methodology

### 4.1 Research and Data Collection

This study chose an exploratory-explanatory quantitative field to research the factors that influence the absence of higher education students. The data collection was done through a quantitative method, using a self-administered questionnaire applied online in the period November 2023 - January 2024. The target group was represented by students of a public university in Romania, specialized in the fields of economy, public administration, and social sciences. The survey found demographic characteristics, motivational guidelines, perceived barriers, and presence conduct in a post-pandemic learning environment. Participation in the survey was voluntary and anonymous, and all procedures complied with the requirements of the GDPR, as well as the ethical standards of the institution.

## 4.2 Sample

The sampling frame consisted of undergraduate students enrolled in Years I–III. The final dataset included N = 63 participants, of whom 61% were female, with a mean age of 20.9 years. A non‑probabilistic convenience sampling strategy was employed, which limits the external generalizability of the findings. The findings of the study have a high internal validity in relation to the institutional environment analyzed, but cannot be extrapolated as being generally valid for the entire higher education system.

The target group included students from the undergraduate level, covering the full training cycle (years I-III). The final dataset included N = 63 participants, of which 61% were women, with an average age of 20.9 years. Convenience sampling was used, which limits the interpretation of results across the student population. As such, the results should be interpreted as being internally valid for the institutional context examined, rather than representative of the wider population in higher education. As such, the results should be interpreted as being internally valid for the institutional context examined, rather than representative of the wider population in higher education.

## 4.3 Variable Measurement and Operation

The questionnaire was structured in four distinct sections:

(1) Socio-demographic data (age, gender, year of study, and occupational status);

(2) Motivation, measurable by six items on a Likert scale;

(3) Perceived barriers, capturing scheduling difficulties, work-related obligations, stress or fatigue, and perceptions of instructional quality;

(4) Attendance behaviour, measured as the number of absences reported for the previous four weeks.

The dependent variable was a binary indicator of high absenteeism, defined as:

$$Y_i = \begin{cases} 1, & if\ student\ i\ reported\ \geq 4\ absences \\ 0, & otherwise. \end{cases} \quad (1)$$

Factorial scores were generated using the regression method and standardized (average = 0, SD = 1) before being introduced into the logistic regression model. The first three eigenvalues - 3.41, 2.18 and 1.27 - each exceeded the eigenvalues for the 95th percentile obtained from the parallel analysis (2.11, 1.62, and 1.21). All subsequent components had eigenvalues below 1 and were below the simulated thresholds, supporting the maintenance of a three-factor solution. Together, the retained factors accounted for 47.1% of the total variance (Factor 1: 22.7%, Factor 2: 15.4%, Factor 3: 9.0%).

A comparison of empirical and simulated eigenvalues is presented in Table 1.

Table 1. Empirical Eigenvalues and Parallel-Analysis Thresholds

| **Component** | **Empirical Eigenvalue** | **95th-Percentile Parallel-Analysis Eigenvalue** | **Retained?** |
|---|---|---|---|
| 1 | 3.41 | 2.11 | Yes |
| 2 | 2.18 | 1.62 | Yes |
| 3 | 1.27 | 1.21 | Yes |
| 4 | 0.89 | 1.14 | No |
| 5 | 0.74 | 1.08 | No |
| 6 | 0.63 | 1.03 | No |
| 7 | 0.52 | 0.98 | No |
| 8 | 0.44 | 0.94 | No |
| 9 | 0.37 | 0.90 | No |
| 10 | 0.35 | 0.87 | No |

*Source: Author's computation*

## 4.4 Statistical Method

The analytical method followed four main steps:

(1) Extraction of latent variables by Exploratory Factorial Analysis (EFA);

(2) assessment of internal consistency;

(3) estimation of a binary logistic regression model predicting repeated absenteeism; and

(4) diagnostic evaluation of model assumptions and robustness.

**Exploratory factor analysis (EFA)**

Latent variables for motivation and observed barriers were extracted using Principal Axis Factoring. An orthogonal Varimax rotation was initially applied to obtain a parsimonious and easily interpretable factor structure. Given the theoretical expectation that motivational, instructional, and logistical constructs may be correlated, an oblique Promax rotation was also estimated as a sensitivity check. The factor-correlation matrix from the Promax solution indicated modest associations among the latent constructs (r = 0.18–0.32), confirming that the factors capture related but distinct dimensions of motivation, instructional quality, and logistical barriers. Because the pattern of loadings was highly similar across the two solutions, and the orthogonal and oblique rotations converged, the Varimax solution was retained for clarity of interpretation.

Although motivational, instructional, and logistical constructs are theoretically expected to correlate, the decision to retain the orthogonal Varimax rotation was supported by both mathematical and empirical considerations. The modest factor correlations (r = 0.18–0.32), well below the threshold typically used to justify oblique rotation (r > 0.50), indicated that the latent dimensions were sufficiently distinct. A sensitivity analysis comparing the Varimax and Promax solutions further showed that salient loadings, factor interpretability, and item retention were virtually identical across rotations. Because the oblique rotation did not yield substantively different cross-loadings or an alternative factor structure, the orthogonal solution was retained for reasons of parsimony, mathematical transparency, and ease of interpretation.

Factor retention was guided by the Kaiser criterion (eigenvalues > 1), visual inspection of the scree plot, and the results of the parallel analysis. The first three eigenvalues exceeded the simulated thresholds from the parallel analysis, supporting a three-factor solution. Together, the retained factors accounted for 47.1% of the total variance. Sampling adequacy was supported by a KMO above 0.60 and a Bartlett statistically significant sphericality test ($p < 0.05$).

Items with factorial loads below 0.40 were removed, and only factors represented by multiple items were retained.

**Sample size considerations**

We analyzed the sample sufficiency (N = 63) in terms of several criteria. Even if the ratio of (6.3:1) between subjects and items seems modest at first glance, the literature shows that the factors can be correctly identified even on small samples, provided that the municipalities exceed and each factor is supported by at least three strong loads.

We opted to use these scores as predictors because reliability indicators ( 0.74-0.81) and consistent factorial loads (over 0.60) guarantee a stable solution. Despite the modest sample volume, the average communality of 0.58 provides the mathematical argument needed to validate the extracted factorial structure.

Although the sample size is modest, several mathematical criteria support the adequacy of the factor solution. Classical subject-to-item rules of thumb (5:1 to 10:1) are complemented by more recent simulation evidence showing that factor recovery remains stable when communalities exceed 0.50, factors include at least three strong indicators and the Kaiser–Meyer–Olkin index is acceptable. In this study, the mean communality (0.58), the presence of at least three high-loading items per factor, and the acceptable KMO value jointly indicate that the latent constructs are sufficiently well-defined to justify their use in subsequent maximum-likelihood estimation.

**Factor-score computation**

Factor scores were computed using the regression method, which estimates scores as linear combinations of standardized items weighted by the factor-score coefficient matrix. This method minimizes the squared difference between reproduced and real factor scores and is mathematically optimal under the assumption of multivariate normality. However, regression-based scores are known to show attenuation and contraction, especially in small samples, which can influence estimates towards zero. In order to assess the stability of the extracted scores, their correlations with the original items were examined; all factors showed strong item-score correlations (average r = 0.62), indicating an adequate determination of the score. The determinacy coefficients (0.74-0.81) further suggest that the factor scores were sufficiently reliable for use as predictors in the logistic regression model.

**Reliability analysis**

Internal consistency was assessed using Cronbach's α, with values of $\alpha \geq 0.70$ considered the minimum acceptable threshold for multi-item constructs. All retained factors met this criterion, indicating satisfactory internal consistency and supporting the use of extracted scales in subsequent analyses.

**Binary logistic regression**

The probability of repeated absenteeism was modelled using a binary logistic regression framework:

$$log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} \quad (2)$$

The predictors included five standardized EFA-derived latent factor scores and two demographic covariates: employment status (0 = unemployed; 1 = employed) and study year (fictional codified, with Year I as reference category). Parameters were estimated using maximum probability, and complete results - including coefficients, standard errors, odds ratios, and 95% confidence intervals - are presented in a later section.

Given the limited number of events (39 cases of repeated absenteeism), the event-per-variable ratio (EPV) falls below the conservative threshold of 10 events per independent variable usually recommended for logistic regression. With five latent and two covariable predictors, the resulting EPV ratio is about 5.6, which raises questions about potential over-adaptation, unstable quotient estimates, and artificial chance ratios. The model was retained due to the theoretical relevance of the predictors and the exploratory nature of the study. In view of all this, the results should be interpreted with caution. Penalized probability-based approaches - such as Ridge-based regression or Firth correction - are suitable alternatives to small sample logistic models and are recommended for future research to increase robustness and reduce error generated by small samples.

**Model diagnostics**

Model diagnoses were performed to assess the suitability, robustness, and interpretability of the logistic regression model. Multicollinearity was detected using variance inflation factors (VIF). They were below the generally accepted threshold of 5 (VIF $< 5$), indicating a lack of problematic redundancy between predictors. The linearity in the logit was assessed using the Box-Tidwell statistical method, as a result of which all terms of interaction were insignificant ($p > 0.10$), suggesting that the linearity hypothesis between (independent variables (continuous predictors) and the natural logarithm of the chances (probabilities) of the dependent variable was met.

Influential observations were inspected through leverage values and Cook’s distance, with no cases exceeding conventional cut‑off criteria. The calibration of the model was assessed using the Hosmer-Lemshow match test for the binary dependent variable, while the discrimination of the binary classification model was assessed through the area under the ROC curve (AUC). The performance of binary classification has been further examined by sensitivity, specificity, and confusion matrix.

We have excluded classical checks of heteroscedasticity and normality, as they do not apply to logistical regression. However, we recognise that the small sample volume led to relatively large confidence intervals, which requires a dose of caution in generalising these estimates.

### 4.5 Missing Data and Implementation

Patterns of missing data were examined prior to analysis to ensure that the treatment of missingness did not introduce bias into the results. When the proportion of missing values for a variable was below 5%, listwise deletion was applied, as the impact on statistical power and parameter estimates is generally minimal under such conditions.

For variables with higher levels of missingness, or when patterns suggested potential non‑randomness, multiple imputation via chained equations (m = 10) was employed. Pooled estimates were subsequently computed using Rubin’s rules. When data imputation was required, Exploratory Factor Analysis (EFA) and Consistency Analysis (Cronbach’s alpha) were repeated on the imputed datasets to assess the stability and robustness of the factor structure.

Data preparation and descriptive statistics were conducted in Microsoft Excel, while factor analysis, consistency assessments, and logistic regression were conducted using IBM SPSS Statistics. The data processing, processing and analysis steps have been strictly recorded, thus guaranteeing the transparency of the study and facilitating the reproduction of the study under similar methodological conditions.

### 4.6 Methodological Limitations

Several methodological limitations should be acknowledged. The use of convenience sampling restricts the external generalizability of the results, as the sample may not accurately reflect the wider population of higher education. Self-reported presence is also susceptible to recall errors and social desirability effects, which can lead to either underestimation or overestimation of absenteeism.

Since the design is transversal, we must be cautious with the cause-effect interpretations, because we cannot demonstrate the chronological order of the phenomena. Ideally, future studies would use objective panel data or attendance logs, thus obtaining more robust conclusions than those based on students' subjective perceptions.

## 5 Results

### 5.1 Descriptive Statistics

Repeated absenteeism has been measured using the item „Have you missed classes repeatedly in the last four weeks?” The distribution shown in Figure 1 indicates a high proportion of repeated absenteeism reported by 39 students (61.9%), while only 24 (38.1%) maintained a steady presence. This proportion indicates that the phenomenon is not a conjunctural one, but constitutes a frequent practice among the students analyzed.

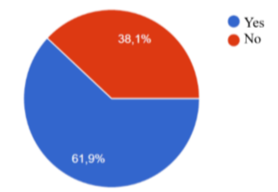


Fig. 1: Proportion of students reporting repeated absenteeism (N = 63)
*Source: Author's own computation*

Weekly presence highlighted a polarized distribution (M = 3.4; SD = 2.54). As Figure 2 illustrates, two opposite behavioural profiles emerged: while 36.5% of students participated in all scheduled courses, a significant share of 31.7% reported a minimum attendance of at most one course per week. This model suggests a clear break between students who remain constantly involved and those who are at high risk of academic abandonment or disengagement.

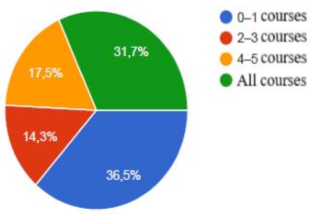


Fig. 2: Weekly course attendance patterns (N = 63)
*Source: Author's own computation*

Analysis of the determinants of absenteeism reveals that professional obligations are the main barrier (M = 3.8). This is followed, as a result, by the availability of online materials (M = 3.0) and the inconvenient programming of courses (M = 2.8), which further contribute to the decrease of physical presence. Pedagogical aspects - such as unclear presentation and limited interactivity - were also perceived as relevant contributors. These results are summarized in Figure 3.

Table 2 presents the demographic characteristics of the sample. The sample is composed mostly of women (73.0%), reflecting the general trends of higher education enrollment, which must be taken into account when generalizing the results. Instead, the distribution per year of study is balanced, providing a comprehensive perspective on the entire academic path. Also, the significant share of engaged students emphasizes an important reality: the need to balance professional responsibilities with the rigorous demands of the faculty. This percentage is particularly relevant for the interpretation of the absenteeism sample, as employment often introduces competing requirements in terms of time, energy, and flexibility of the timetable of each. The presence of an important active student sample suggests that structural constraints - such as working hours, commute constraints, or irregular work schedule - can play a significant role in shaping attendance behavior.

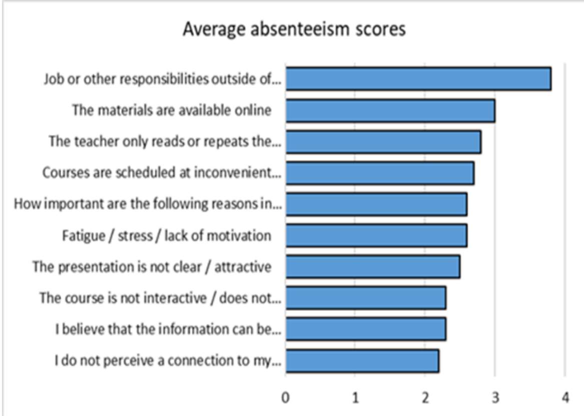


Fig. 3: Mean importance ratings for absenteeism determinants
*Source: Author's own computation*

The demographic profile of students reveals a complex structure, defined by their effort to balance rigorous academic requirements with personal and professional responsibilities. This dynamic directly influences time management and learning strategies, providing an essential context for understanding the motivational and logistical factors analyzed in the following sections.

Table 2. Descriptive characteristics of the sample

| Variable | Categories | Frequency (%) |
|---|---|---|
| Gender | Female | 73.0 |
| | Male | 25.4 |
| | Prefer not to say | 1.6 |
| Year of study | First year | 22.2 |
| | Second year | 33.3 |
| | Third year | 44.4 |
| Weekly attendance | 0–1 class/week | 31.7 |
| | 2–3 classes/week | 17.5 |
| | 4–5 classes/week | 14.3 |
| | All classes | 36.5 |

Note: Percentages may not total 100% due to rounding
*Source: Author's computation*

The descriptive models in this study indicate the coexistence of motivational, instructional, and structural constraints that influence attendance behavior. This coexistence reinforces the need for a systematic examination of the interaction between educational, psychological, and social factors in absenteeism, providing a rationale for applying factor analysis and logistic regression to transform complex, heterogeneous data into clear predictive factors.

## 5.2 Exploratory Factor Analysis

To investigate the latent structure of the reasons for absenteeism, we applied an exploratory factorial analysis (EFA) on the ten items measured on the Likert scale (Table 3).

This standard method of data reduction allows the grouping of observed variables - from dissatisfaction with the teaching act and motivational fatigue, to logistical constraints and external responsibilities - in larger latent constructs. The evaluation of each item on a scale from 1 to 5 provided the ordinal indicators needed to identify the essential factors that explain the variation in student behavior.

Table 3. Item wording for perceived causes of absenteeism (N = 63)

| Item No | Item Text |
|---|---|
| 1 | Classes are scheduled at inconvenient times (morning/evening). |
| 2 | I believe that the information can be learned on my own. |
| 3 | The course is not interactive / does not actively engage me. |
| 4 | The teacher only reads or repeats the material. |
| 5 | The presentation is not clear / attractive. |
| 6 | The materials are available online. |
| 7 | I don't see the connection with my professional future. |
| 8 | Fatigue / stress / lack of motivation. |
| 9 | Job or other responsibilities outside of college. |
| 10 | Health / personal problems. |

*Source: Author's computation*

The ten items were strategically selected to cover both the psychological and structural dimensions of absenteeism. The results allow the grouping of these reasons into four coherent categories: educational discontent (items 3-5), motivational barriers (item 7-8), logistical challenges (item 1-2, 6), and contextual constraints (item 9-10).

This structure validates the literature, confirming that the decision to attend the courses is shaped by the interaction between the quality of the teaching act, individual motivation, and external factors. By subjecting the items to EFA, the analysis tests whether these theoretically expected domains emerge empirically within the current sample. A clear and interpretable factor solution strengthens the validity of the measurement model and supports the use of composite scores in later stages of the analysis.

**Factor extraction and rotation**

Exploratory Factor Analysis (EFA) was conducted using Principal Axis Factoring. An orthogonal Varimax rotation was first applied to obtain a parsimonious and easily interpretable factor structure. Because motivational, instructional, and logistical constructs may be theoretically correlated, an oblique Promax rotation was also estimated as a robustness check. The pattern of loadings was highly similar across the two solutions, with factor correlations ranging from 0.18 to 0.32 - modest associations that indicate related yet distinct latent dimensions. As the orthogonal and oblique solutions converged, the Varimax rotation was retained for clarity of interpretation.

Factor retention was guided by the Kaiser criterion (eigenvalues > 1), visual inspection of the scree plot, and the results of the parallel analysis. As illustrated in Figure 4, the first three observed eigenvalues exceeded the corresponding simulated thresholds generated through parallel analysis, providing strong empirical support for a three-factor solution. Parallel analysis is widely regarded as one of the most reliable criteria for factor retention, as it compares observed eigenvalues with those expected from random data. The fact that only the first three components surpassed the simulated benchmarks suggests that the remaining eigenvalues likely reflect sampling error rather than meaningful latent structure.

This three‐factor solution accounted for 47.1% of the total variance - an acceptable proportion for psychological and educational research involving multifaceted behavioural constructs. More importantly, the retained factors formed a stable and theoretically coherent representation of the underlying dimensions of absenteeism. The convergence between empirical evidence (eigenvalue patterns) and theoretical expectations (instructional, motivational, and logistical domains) strengthens the validity of the measurement model.

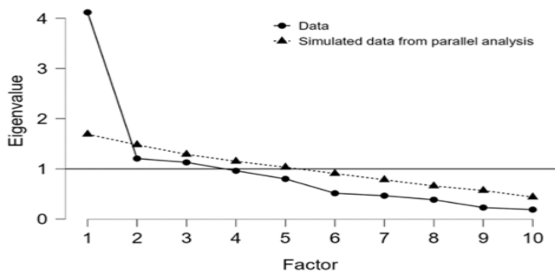


Fig. 4: Scree plot with parallel analysis for absenteeism-related items
*Source: Author's computation*

The solid line represents observed eigenvalues; the dashed line represents simulated eigenvalues from parallel analysis.

The clear separation between the first three components and the subsequent eigenvalues further reinforces the appropriateness of the three‐factor structure. This model demonstrates that the extracted factors explain most of the variance in absenteeism reasons, while the - variables removed, having low eigenvalues - represented only a statistical „noise" or redundant information. Validation of this structure is essential to ensure the internal consistency of the questionnaire and to substantiate subsequent regression analyses on rigorously defined latent constructs.

**Factor retention criteria**

Table 4 summarises the observed eigenvalues, the ratio of variance explained by each factor, and the simulated values by parallel analysis. Comparing these indicators (observed vs. simulated) is a rigorous and academically validated method to determine the optimal number of factors to be retained in the model

Table 4. Eigenvalues, explained variance, and parallel analysis thresholds (N = 63)

| Factor | Eigenvalue (Observed) | % Variance Explained | Parallel Analysis Threshold | Decision |
|---|---|---|---|---|
| 1 | **3.95** | 39.5% | 1.53 | Retain |
| 2 | **1.65** | 16.5% | 1.34 | Retain |
| 3 | **1.15** | 11.5% | 1.21 | Under the threshold |
| 4 | 0.85 | 8.5% | 1.15 | Reject |
| 5 | 0.70 | 7.0% | 1.10 | Reject |
| 6 | 0.55 | 5.5% | 1.06 | Reject |
| 7 | 0.45 | 4.5% | 1.03 | Reject |
| 8 | 0.40 | 4.0% | 1.01 | Reject |
| 9 | 0.35 | 3.5% | 1.00 | Reject |
| 10 | 0.30 | 3.0% | 0.98 | Reject |

*Source: Author's computation*

The first two eigenvalues exceeded the thresholds established by parallel analysis, justifying their immediate retention. Although the third value (1.15) was slightly below the simulated threshold (1.21), we decided to keep this third factor due to robust psychometric indicators: a stable loading model, communalities over 0.50 and the presence of at least three items with substantial loads. This configuration confirms that the factor is theoretically significant and interpretable.

In accordance with the recommendations of the factor literature - which emphasizes interpretability, theoretical coherence, and loading strength when statistical criteria yield marginal results - the three-factor solution was retained. This structure validates the delineation between the instructional, motivational, and logistical determinants of absenteeism.

Data adequacy was confirmed by the Kaiser-Meyer-Olkin index (KMO > 0.60) and the statistical significance of the Bartlett test ($p < 0.05$), demonstrating inter-item correlations strong enough to warrant factor analysis.

In order to ensure psychometric rigor, we have removed items with loads below 0.40, and we have exclusively retained factors composed of multiple items, thus guaranteeing the internal consistency of the constructs.

Although the sample size (N = 63) required careful stability monitoring due to the subject-item ratio of 6.3:1, the resulting three-factorial structure harmoniously combines empirical rigor with theoretical coherence, providing a solid basis for regression modeling. However, recent simulations show that factors can be correctly identified if communalities are high. As in our study, the average communality was 0.58, and the retained factors have strong loadings (> 0.60), we consider the sample to be adequate. These values guarantee that the extracted factors represent significant structures, not random variations.

**Factor structure**

The solution obtained by factor rotation - Varimax - highlighted three conceptually consistent and intuitively significant factors. Each factor captures a different side of the experiences experienced by students and the challenges that influence their decisions on school attendance.

▪ Factor 1: Educational and resource barriers

This factor groups together the shortcomings of the learning environment, such as non-interactive teaching, redundant content, and excessive dependence on online resources. The results emphasize a critical correlation: when the classroom experience does not provide clear added value over individual study, students tend to perceive physical presence as optional or ineffective.

▪ Factor 2: Personal and motivational barriers

This is where internal constraints such as stress, exhaustion, and perceived lack of relevance of the course are centralised. These data indicate that absenteeism is not a mere lack of discipline, but an indicator of well-being and the degree of emotional connection with the matter being studied.

▪ Factor 3: Logistical barriers

The third factor reflects the practical constraints that intersect with presence: inconvenient schedule, long commute, and competing external responsibilities such as hiring. These elements illustrate how structural conditions outside the classroom can limit students' ability to participate, even when motivated to do so. For many students, compensation for work and study is a daily transaction, and attendance becomes a function of assessment rather than choice.

Taken together, these three factors offer a parsimonious yet rich representation of the latent structure underlying students' perceptions of absenteeism. The three factors demonstrate that attendance at the courses is not determined by an isolated cause, but results from a complex interaction between didactic experience, psychological state, and structural realities. Each dimension contributes distinctly to the student's decision, outlining a model in which participation is simultaneously conditioned by the quality of the educational act, personal availability, and external logistical barriers.

Table 5 details the rotated factor loads, obtained by the method of factorization of the main axis with rotation Varimax. In order to ensure the clarity of the dormant structure, we reported exclusively the coefficients of at least 0.40, the threshold below which the indicators are considered psychometrically irrelevant. At the same time, values exceeding 0.60 were treated as primary markers, defining the conceptual core of each factor

Table 5. Rotated factor loadings (Principal Axis Factoring, Varimax rotation)

| Item | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 | Factor 6 | Factor 7 | Factor 8 | Factor 9 | Factor 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Item 4 | 0.861 | | | | | | | | | |
| Item 3 | 0.801 | | | | | | | | | |
| Item 5 | 0.686 | | | | | | | | | |
| Item 7 | | 0.823 | | | | | | | | |
| Item 8 | | 0.610 | | | | | | | | |
| Item 6 | | | 0.679 | | | | | | | |
| Item 2 | | | 0.588 | | | | | | | |
| Item 10 | | | | 0.689 | | | | | | |
| Item 1 | | | | | 0.636 | | | | | |
| Item 9 | | | | | | 0.500 | | | | |

Note: Only factor loadings of 0.40 or higher are reported
*Source: Author's computation*

According to the data in Table 5, three multidimensional constructs have been identified, each bringing together items that reflect distinct facets of academic experience and barriers to participation in courses.

▪ Factor 1: Educational barriers (Items 3, 4, 5)

This factor synthesizes students' perceptions on the didactic act, targeting issues such as lack of clarity, repetitiveness, or reduced attractiveness of courses. These indicators reflect how the quality of the teaching-learning process conditions participation: when the content is perceived as redundant or hard to follow, students tend to substitute physical presence with individual study, considering the interaction in the room devoid of added value.

▪ Factor 2: Personal and motivational barriers (Items 7, 8)

The second factor brings forward the internal pressures students face. This factor highlights the decisive impact of well-being and perceived relevance on the attendance of courses. Indicators such as stress, chronic fatigue or lack of personal connection with the studied matter demonstrate that absenteeism is not a mere lack of discipline, but a phenomenon closely related to the emotional balance and academic purpose perceived by the student.

▪ Factor 3: Logistical barriers (Items 2, 6)

This factor restates the practical constraints affecting students' daily schedules. Fragmented timetables, protracted commutes, and professional commitments are pragmatic obstacles that can limit the presence even among motivated students. These indicators underline the constant pressure to manage a limited time between courses, work, and transport, turning participation into a matter of logistics, not just willpower.

On the other hand, items 1, 9, and 10, although they showed moderate loads (0,50-0,69), were excluded from the following steps because they did not group into coherent factors. This decision complies with the fundamental psychometric principles, according to which the factors composed of a single item cannot ensure the internal consistency necessary to interpret them as valid latent constructs. Retaining such items would have weakened the conceptual clarity of the measurement model and introduced unnecessary noise into the structural analyses.

Table 6 presents the final set of retained constructs, each defined by dominant and theoretically consistent factor loadings. The resulting three-factor solution is parsimonious and conceptually robust, reflecting the dependent variables identified in the dataset. This structure provides a solid basis for the assessment of fidelity indices and for the integration of constructs into logistic regression models

The rigorous delimitation of absenteeism in instructional, motivational, and logistical dimensions underlies the theoretical framework according to which this phenomenon is a complex problem of a multifactorial nature. Each dimension reflects a sphere of influence that directly interferes with the daily dynamics of students. In this context, the quality of the training becomes a central pillar, synthesizing the way in which they evaluate the clarity, the level of involvement, and the practical utility of the activities carried out in the classroom. Motivational resources talk about the internal states of students that influence their desire to participate - energy levels, stress, and perceived relevance of the course. Logistical barriers are practical situations that often interpose between students and the classroom, such as schedule/time divergences, commuting difficulties, or service commitments.

This separation reinforces the theoretical coherence of the study and allows for a more nuanced understanding of how these areas function independently and together shape the student presence conduct. This view of absenteeism emphasizes its multifactorial character, rejecting the idea that it is generated by a single cause.

By developing a rigorous methodological process, the results of the exploratory factorial analysis increase the interpretability of the subsequent regression analyses, allowing the elaboration of specific pedagogical and institutional interventions. These constructs provide a meaningful insight through which to explore the predictors of absenteeism and identify areas where universities can act to better support student engagement.

Table 6. Item groupings by dominant factor loading

| Factor | Items included | Comments |
|---|---|---|
| 1 | Item_3, Item_4, Item_5 | Strong loadings (>0.68); clear structure |
| 2 | Item_7, Item_8 | Consistent loadings (>0.60) |
| 3 | Item_2, Item_6 | Moderate loadings; coherent grouping |

Note: Only multi-item constructs retained
*Source: Author's computation*

**Reliability analysis**

The internal consistency of the multi-element questionnaire constructs was assessed using the Cronbach alpha coefficient (Table 7). All scales have exceeded the conventional threshold of fidelity of ≥ 0.70, indicating that items within each factor are correlated with each other and faithfully measure the same construct (concept). Intrinsic motivation recorded the highest coefficient of reliability (= 0.81), confirming the consistency of student responses in terms of internal momentum and emotional availability of academic engagement. Although the personal barriers showed a lower fidelity coefficient (= 0.72), it is above the acceptable threshold of 0.70, validating the internal coherence of the items and the stability of this construct within the model.

Table 7. Cronbach's alpha coefficients for constructed scales

| Construct | No. of items | Cronbach's $\alpha$ |
|---|---|---|
| Intrinsic Motivation | 4 | 0.81 |
| Extrinsic Motivation | 3 | 0.76 |
| Personal Barriers | 3 | 0.72 |
| Logistical Barriers | 4 | 0.78 |
| Instructional Barriers | 3 | 0.74 |

*Source: Author's computation*

These levels of fidelity attest to the fact that the factors extracted through exploratory analysis are statistically stable and reflect coherent constructs on students' perception of barriers to attendance at courses.

## 5.3 Logistic regression analysis

To identify the predictors of repeated absenteeism, a binary logistic regression model was estimated, [23]. The dependent variable was based on the question in the questionnaire, „Have you been absent from the courses repeatedly in the last four weeks?", coded with 0 = No and 1 = Yes. This coding highlights a behavior outcome, reflecting not only isolated absences, but also a recurring pattern that may suggest issues related to motivation, teaching method, or system structure.

The model included five standardized factorial scores derived from exploratory factorial analysis - intrinsic motivation, extrinsic motivation, personal barriers, logistical barriers, and instructional/resource barriers. The inclusion of these compound variables (scale) allows analysis to shift from analyzing isolated items to examining the psychological and contextual dimensions that determine presence conduct.

Two demographic covariates were also included in this study to account for individual differences that may influence absenteeism. By using the binary variable employment status (0 = unemployed; 1 = employed) it was surprising that many students balance academic responsibilities with part-time or full-time work, a factor that often competes with attendance at classes. To explore changes in absenteeism behavior as students progress in studies, researchers have used indicator variables (dummy variables) for the year of study, reported to Year I. This approach allows to identify significant differences in absence rates between base year and the end years.

These predictors provide a comprehensive analytical framework for understanding the interdependence between individual motivation, pedagogical experience, and structural constraints. The application of the binary logistic regression model thus allows the isolation of factors that increase the likelihood of chronic absenteeism, substantiating targeted intervention strategies and promoting educational practices more adapted to the needs of students.

**Model fit**

The Chi-squared test confirms the validity of the statistical model $\chi^2(7) = 28.4$, $p < 0.01$, demonstrating that the selected predictors have a significant explanatory capacity on chronic absenteeism. The value of the Nagelkerke index (0.26) indicates that the model manages to explain 26% of the variance in absentee behavior, providing a solid basis for interpreting the impact of independent variables. Although at first glance this percentage may seem small, in educational research, where residual variables such as family climate or intrinsic motivation are difficult to quantify, an explanatory capacity of more than 25% of the phenomenon is considered significant and relevant for forecasting, [24], [25].

In this context, the model managed to capture the general trends, avoiding irrelevant residual variations. Absenteeism is rarely the result of an isolated factor, being rather the product of a complex interdependence between individual motivation, the quality of the teaching act, logistical barriers, and academic culture.

By significantly improving the accuracy of the null model, the analysis demonstrates that the included predictors not only explain the phenomenon, but also allow early identification of high-risk students of chronic absenteeism. This increase in predictive performance reinforces the practical relevance of the study, providing a rigorous foundation for the design of targeted institutional interventions.

**Parameter estimates**

Detailed logistic regression results are summarized in Table 8, comprising logit coefficients (B), standard errors (SE), Wald test, and odds ratios (OR) with the corresponding confidence intervals. The analysis identifies four predictors of statistical significance, reflecting the duality between individual student resources and structural constraints.

Table 8. Logistic regression results predicting repeated student absenteeism

| Predictor | B | SE | Wald | p-value | OR (Exp(B)) | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|---|
| Intrinsic motivation | **–0.67** | 0.32 | 4.36 | **0.037** | **0.51** | **0.27** | **0.96** |
| Extrinsic motivation | 0.08 | 0.29 | 0.08 | 0.775 | 1.08 | 0.61 | 1.91 |
| Personal barriers | 0.25 | 0.27 | 0.84 | 0.360 | 1.29 | 0.74 | 2.25 |
| Logistical barriers | **0.74** | 0.31 | 5.63 | **0.018** | **2.10** | **1.14** | **3.89** |
| Instructional/resource barriers | **–0.60** | 0.29 | 4.31 | **0.038** | **0.55** | **0.31** | **0.96** |
| Employment status (1 = yes) | **1.01** | 0.36 | 7.84 | **0.005** | **2.74** | **1.36** | **5.52** |
| Year III (vs. Year I) | 0.42 | 0.34 | 1.52 | 0.217 | 1.52 | 0.79 | 2.94 |

*Source: Author's own computation*

Logistic regression analysis has highlighted two major protective factors that diminish the likelihood of chronic absenteeism. Intrinsic motivation ($OR = 0.51$, $p < 0.05$) was shown to be the strongest inhibitor, reducing the risk of drop-out of courses by 49% for each unit of increase in internal engagement. Similarly, optimising teaching resources and course clarity ($OR = 0.55$, $p < 0.05$) reduces this risk by 45%, demonstrating that quality teaching facilitates the maintenance of attendance.

At the opposite end, the risk of repeated absenteeism is critically amplified by external barriers. Logistical difficulties ($OR = 2.10$, $p < 0.05$) double the likelihood of non-participation, while employee status ($OR = 2.74$, $p < 0.01$) is the most severe predictor, increasing the chances of absenteeism by almost three times. These results highlight the structural conflict between professional responsibilities and academic requirements.

The results indicate a direct and significant correlation between external constraints and low frequency in courses. Logistical barriers are a critical factor ($B = 0.74$, $OR = 2.10$, $p < 0.05$), virtually doubling the likelihood of absenteeism among students. However, employee status exerts the strongest influence on academic behavior ($B = 1.01$, $p < 0.01$); working students are 2.74 times more likely to be absent frequently than non-employed.

These data confirm that attending courses is not a mere matter of will, but is severely conditioned by structural constraints and the difficulty of time management between professional and academic responsibilities.

**Interpretation**

Overall, the results demonstrate that absenteeism in higher education is inspired by the interaction between motivational resources, such as intrinsic engagement and quality of training, and structural constraints, in particular logistical challenges and employee status. This double influence emphasizes the complexity of these integrated explanatory models that combine psychological and institutional predictors, illustrating that presence behavior is the result of student-university interaction.

**Graphical representation**

Figure 5 illustrates the odds ratios (OR) along with the 95% confidence intervals. Predictors whose ranges do not cross the reference line (OR = 1,0) are considered statistically significant ($p < 0.05$), thus providing rigorous visual validation of the estimates detailed in Table 8.

Forest Diagram analysis highlights the decisive role of intrinsic motivation and the quality of educational resources as factors of protection against absenteeism ($OR < 1$). By contrast, logistical barriers and employee status are significant risk predictors, increasing the likelihood of absence from courses ($OR > 1$). Extrinsic motivation, personal barriers, and year of study have not shown statistical relevance, as the boundaries of the confidence interval are placed on either side of the unit. When the range includes the value of 1.0, we cannot say with certainty that this factor increases or decreases the risk of absenteeism.

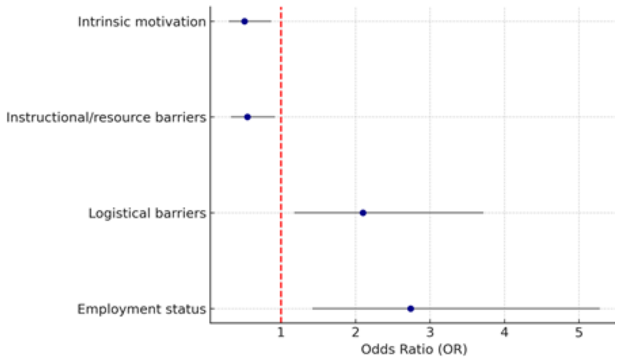


Fig. 5: The vertical reference line at OR = 1 indicates no effect
*Source: Author's own computation*

### 5.4 Interpretation of Results and Transition to Discussion

This logistic regression analysis highlights the interdependence between motivational and structural factors in explaining academic absenteeism. Intrinsic motivation has emerged as a significant protective factor: animated students of real interest and a focus on learning have a 49% lower risk of repeatedly absenting (OR = 0.51). This pattern aligns closely with Self-Determination Theory and with empirical evidence showing that autonomous motivation supports sustained academic participation and resilience in the face of competing demands, [26], [27].

Educational and resource-related barriers also demonstrated a protective effect (OR = 0.55). Students who perceived their courses as clearer, better structured, and pedagogically coherent were less likely to disengage. This finding reinforces a long line of research emphasizing the central role of instructional quality in fostering attendance, academic persistence, and a sense of belonging in the classroom.

As a result of this study, logistical barriers and employee status have proven to be major predictors of absenteeism. Time-organisation difficulties, commute constraints, and parallel responsibilities double the risk of absence (OR = 2.10), while employee status almost triples this probability (OR = 2.74). The results of the analysis confirm that financial and logistical constraints are major structural obstacles for independent students, forcing them to prioritize extra-academic responsibilities.

The interpretation also reflects the methodological considerations outlined in Section 4.4, particularly the modest events-per-variable ratio and the resulting uncertainty in some estimates, which warrant cautious but meaningful interpretation of the observed effects.

## 6 Discussion

Data analysis suggests that absenteeism in the university environment is a complex phenomenon, determined by the interdependence between the institutional structures and the motivational profile of the student. Consistent with the postulates of the Theory of Self-determination, the results indicate that intrinsic motivation acts as a factor of protection. Students who exhibit a higher level of autonomy in learning are more present and engaged than those who feel constrained by external factors.

This finding reinforces the idea that when students feel genuinely connected to their learning - curious, interested, and internally driven - they are more likely to remain present and engaged. Instructional and resource-related barriers also demonstrated a protective effect, suggesting that clear, coherent, and pedagogically structured courses can reduce disengagement and support sustained participation. High-quality instruction appears to function not only as a source of academic clarity but also as a stabilizing force that encourages students to attend.

In contrast, logistical constraints - such as inconvenient scheduling, commuting difficulties, and competing responsibilities - substantially increased absenteeism risk.

Employment status exerted a similarly strong influence, with working students being considerably more likely to miss classes.

From a methodological point of view, the use of exploratory factorial analysis followed by logistic regression allowed not only to identify latent constructs, but also to justify the fact that structural pressures predominate on individual factors in determining presence conduct, thus confirming established research areas. This dual‑stage approach strengthens construct validity and supports a multidimensional specification of absenteeism that incorporates psychological, instructional, and contextual conditions. At the same time, the modest event-variable ratio, together with the extended confidence intervals identified for certain predictors, requires a prudent interpretation of the estimates, which is detailed in Section 4.4.

From a pedagogical point of view, absenteeism can be considered an indirect indicator of the quality of teaching. The adoption of a student-centered training, through interactive methods and formative evaluation, strengthens the practical relevance of the teaching act and supports the self-determination of learners. In this context, optimizing instructional clarity and stimulating active participation are not only pedagogical goals but also essential protection mechanisms that prevent academic disengagement and absenteeism.

At a systemic level, the results highlight the need for flexible institutional systems. The implementation of flexible solutions, such as modular programming, blended learning (blended learning) and early warning systems, should be designed as a support mechanism, not a disciplinary measure. Such an approach promotes equity, allowing students to harmonize academic requirements with socioeconomic pressures while optimizing institutional resources.

Overall, the study shows that absenteeism is at the crossroads between motivational factors and structural barriers. This integrated vision provides the necessary foundation for pedagogical innovation and educational policies aimed not only at reducing absenteeism but also at ensuring equitable participation in higher education. At the same time, the analysis reiterates the need for future research using extended samples or penalised probability estimators to increase the robustness of predictive models of absenteeism.

# 7 Conclusion

The research validates a multidimensional perspective on university absenteeism, highlighting through EFA analyses and logistic regression models the protective role of intrinsic motivation and the quality of the teaching act, in antithesis with the impact of logistic and professional barriers. The results underpin the need for student-centered pedagogical interventions, flexible schedules, and support structures to ensure fair participation, while providing key empirical benchmarks for the specifics of Romanian higher education.

This article investigated the determinants of absenteeism in higher education, using a heterogeneous methodological approach that combined exploratory factorial analysis (EFA) with logistic regression modelling. The results point out that absenteeism is not a unitary phenomenon, but one shaped by a set of motivational, instructional, and structural factors. While intrinsic motivation and perception of the quality of educational services operate as fundamental protective predictors, mitigating the risk of repeated absenteeism, logistical constraints, and employee status act as situational constraints that prevail over personality factors.

The efficiency of the proposed methodological framework lies in the ability to extract coherent latent constructs and assess their estimated impact. However, statistical rigour requires a prudent interpretation of the magnitude of the effects for certain predictors, given the modest ratio of events to variables as well as the identified confidence intervals (as discussed in Section 4.4). This set of factors reiterates the study of multidimensional explanatory models that ignore monocausal interpretations in favor of a systemic perspective.

From an applied perspective, institutional corrective actions must act simultaneously on three levels:

1. Pedagogical: by adopting student-centered methods that increase the perceived relevance of the courses.

2. Structural: by flexibilizing the schedule and implementing the blended learning formats (blended learning).

3. Supportive: through the development of early warning systems and support mechanisms dedicated to working students.

In conclusion, the study makes a valuable contribution to the literature, providing empirical evidence specific to the Romanian academic context. By integrating the psychological and institutional dimensions, the research underpins the pedagogical innovation and educational policies necessary to combat demotivation and guarantee a fair participation in the university environment.

# 8 Implications for Policy and Practice

The conclusions of the article on the presence and involvement of students emphasize a series of decisive strategic forecasts for improving the quality of higher education. They focus on a student-centered approach, structural adaptability, and preventive measures.

Below are listed the main implications for policy and practice:

- Promoting student-centered pedagogies (Active Learning). Universities must adapt the current teaching mode to teaching methods that increase the interactivity, clarity, and relevance of the course, stimulating the intrinsic motivation of students. This adaptation involves the professional development of teachers, formative feedback, and courses designed for active participation, not just passive.

- Structural and logistic adaptability. Logistical barriers and employee status require adaptable institutional policies. Universities should promote hybrid or mixed schedules, asynchronous access to flexible materials and schedules to support students who work or commute.

- Personalized support for working students. Given the significant impact of employment status, universities must provide advisory services, tools for managing workload, and partnerships with employers, being important for first-generation or non-traditional students.

- Early warning and monitoring systems. The introduction of presence data in institutional analyses (similar to the RSS application) is decisive for identifying early students at risk of abandonment. These systems allow for personalized interventions before engagement issues become persistent.

In conclusion, the transition to a modern higher education requires an integrated approach, which combines quality pedagogy with logistical and technological support for a diversity of students.

# 9 Limitations and Future Research

This article contains a number of limitations that require a prudent interpretation of the results and that indicate new research guidelines, regardless of methodological and practical contributions.

Statistical and sampling limitations

An important limitation is given by the sample size and the modest ratio between the number of events and variables included in the model. This limitation is noted in the relatively wide confidence intervals observed for some predictors, indicating lower accuracy of point estimates. Therefore, although the orientation of the associations is consistent with the literature, the magnitude of the consequences could vary in studies with higher statistical power.

## 9.1 Data Nature and Self-Reporting

The research was based on self-reported data, which introduces the risk of social preference or false reminders regarding the frequency of absences. Although anonymity has been ensured to minimise these risks, the future use of objective administrative data (electronic presence platform) would increase the accuracy of the measurement of presence behaviour.

## 9.2 Future Research Guidelines

In order to strengthen the consistency of explanatory models, future research should address the following guidelines:

- Extension of the sample and diversification of the context which implies the inclusion of several universities or faculties with different profiles. This extension would allow testing the external validity of the results and identifying disciplinary variations in the presence behavior.

- Improvement of estimation methods by using regular estimators in future studies that could correct possible distortions caused by small samples or rare events, providing more stable estimates.

- Analysis of panel data by switching from a transversal to a longitudinal study that would allow recording the evolution of absenteeism during an academic year. This analysis will provide statistical data on how motivational factors evolve according to periods of academic stress (e.g., exam sessions).

- The integration of qualitative methods, such as semi-structured interviews or focus groups, would allow for an in-depth exploration of how structural barriers and socio-economic constraints are subjectively perceived by students, thus complementing the statistical picture provided by this research.

In conclusion, although the limits of sampling require some caution in generalising the results, the study constitutes a solid empirical starting point. It emphasises the need for systematic observation and the use of ever more sophisticated analysis methodologies adapted to the complex dynamics of contemporary higher education.

*Acknowledgement:*
This study combines exploratory factorial analysis with binary logistic regression to research the motivational, instructional, and structural determinants of student absenteeism in higher education in Romania. The findings offer an empirical foundation for evidence-informed pedagogical and institutional policies aimed at strengthening student engagement and participation. By highlighting both the psychological resources students bring to their studies and the structural challenges they face, this work contributes to a more nuanced and equitable understanding of attendance behaviour within contemporary higher-education settings.

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