THE GREEK DROPOUT TOOL: EXAMINING ITS ADAPTATION AND VALIDITY

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Abstract

The issue of student dropout in higher education represents a critical challenge for both national and European academic communities. Despite extensive research on this phenomenon, the precise factors contributing to dropout remain elusive, and standardized instruments for its assessment vary across contexts and lack cross-context consensus. This study introduces the development of a 15-item questionnaire, specifically designed to identify the factors driving dropout among university students. The questionnaire was distributed to a sample of 3,099 students from all departments of the University of Patras. To evaluate the adaptation and validity of the Greek Dropout Tool, confirmatory factor analysis and item response theory were employed. Additionally, the study integrated three established tools—the Burnout Assessment Tool, the Utrecht Work Engagement Scale, and the Hospital Anxiety and Depression Scale (HADS)—to explore the relationships between dropout and related phenomena. The findings provide insights into the underlying causes of dropout and contribute to the development of targeted interventions.

Keywords: *drop out, adaptation, validity, reliability*

1. INTRODUCTION

The phenomenon of student dropout is a highly complex issue which does not have a clear definition and is recognized as a big challenge in both European and international academic community. This complexity is highly illustrated in data-driven studies which describe dropout as a multidimensional phenomenon driven by academic, behavioral, and contextual predictors rather than a single explanatory factor [1]. Empirical research from Greece, also, supports this perspective, showing that dropout is influenced by different factors, and emphasizes the need for its early investigation [2,3]. According to the data from the National Authority for Higher Education [4], the number of the registered students in Greek universities is 695,678, of which 361,937 (52.03%) are within the maximum study duration prescribed by law, while 333,741(47.97%) students have exceeded the maximum duration. It is a reality that over the last ten years, students outside the standard semesters have outnumbered those studying within the expected timeframe. For this reason, the National Authority for Higher Education estimates that the percentage of students at risk stands at a staggering 46% (324,488 students).

Despite numerous references to this phenomenon and many studies conducted from 1950s to the present, with the aim to uncover its causes [5,6,7,8,9,10], a universally accepted set of factors that contribute to students' dropout, has not yet been established. One theoretical framework that attempts to explain this issue is Tinto's [11] model of long-term withdrawal from an educational institution. According to this model, a student's decision to drop out of the studies is influenced by the level of integration into both the academic (achievement of academic goals) and social (relationships with peers and faculty members) environment of the university. The higher a student's level of integration, the greater the likelihood of successfully completing the studies.

Based on this framework, many researchers have emphasized the importance of various forms of student support in achieving academic goals. According to Krishnan, Venugopalan and Sahib [12], the main cause of student dropout is the lack of parental support, a finding which aligns with the conclusions of Benito-Gomez et al. [13], who highlight the role of parental involvement in student retention. In the same line of argument, Van der Ploeg, Linden and Teakel [14] focus on the need for universities to establish effective policies that support students in achieving academic goals and they discuss the role of institutional interventions in promoting academic persistence.

Similarly, Van Zyl and Blaauw [15] underscore the importance of academic and institutional support during the transition to higher education, conducting a survey among students who took part in extended orientation programs and those who did not. According to the results of the study, students who participated in these programs had a better academic behavior. Some years later, Petronela et al. [16] presented a proposal for an interactive platform that could add substantial value to the orientation process of high school graduates, helping them make more informed decisions about their choice of university study programs.

On the other hand, many researchers focus on the crucial role of institutional factors in student retention and academic success. Osman et al. [17] identified curriculum, assessment, classroom experience, and student support services as four key areas that significantly impact persistence and contribute to student engagement and achievement. Additionally, Cross and Carman [18] uncovered a strong positive relationship between faculty diversity and student outcomes, particularly among underrepresented groups. Increased faculty diversity has been linked to higher graduation and transfer rates, as well as lower dropout rates, highlighting the importance of inclusive educational environments.

Moreover, student dropout rates are a significant concern for educational institutions as they can negatively impact accreditation and reputation [19]. To address this, several studies have focused on developing predictive models to identify students at risk of dropping out [20]. Nguyen et al. [21] used machine learning and deep learning techniques to develop an effective model for identifying students who dropout of university, with the aim of reducing the negative impact on institutional success. Similarly, Kemper, Vorhoff and Wigger [22] applied logistic regression and decision trees to predict student dropout, demonstrating the potential of predictive models to help mitigate dropout rates.

What is more, a review of the literature reveals the efforts of many researchers to examine a possible relationship between dropout and academic engagement and dropout and academic burnout. Bulotaitė et al. [23] attempted to measure students' engagement in combination with other psychological factors, while Lerdpornkulrat, Koul and Poondei [24] tried to investigate students' engagement levels in relation to classroom climate and the institutional goals. Finally, Cortes, Mostert and Els [25] aimed to determine whether core self-evaluation traits, burnout, disengagement, social support, and career decision-making difficulties serve as significant predictors of university students' intention to drop out.

This study, based on previous research, focuses on five key factors that directly influence the dropout phenomenon: academic, personal, institutional, social, and economic [2,3]. The ad hoc 15-questionnaire, called APrISE-15 Dropout Tool (Appendix), represents these five critical dimensions with three items in each category. The aim of this study is to evaluate its adaptation and its validity in the Greek context employing confirmatory factor analysis and item response theory. Additionally, three tools—the Burnout Assessment Tool [26,27], the Utrecht Work Engagement Scale [28], and the Hospital Anxiety and Depression Scale (HADS) [29,30]—were integrated to examine the relationships between dropout and related phenomena. The findings offer valuable insights into the underlying causes of dropout and contribute to the development of targeted interventions.

2. METHODOLOGY

To develop the APrISE-15 Dropout Tool measuring the tendency towards student's dropout, we categorized the factors influencing dropout rates, exactly as in the study using the 69-question questionnaire [2,3]:

- Academic Factor: Three questions regarding satisfaction with the level of studies, feedback from professors on tests and assignments, and the extent to which studies contribute to solving complex daily problems.
- Personal Factor: Three questions concerning feelings of disappointment, the effectiveness of handling studies, and the likelihood of abandoning studies.
- Institutional Factor: Three questions about students' satisfaction with university operations and infrastructure, the university's support for academic success, and general well-being.

- Social Factor: Three questions about the level of relationships and collaboration between students and family, students and friendships outside the university and relationships between students and professors.
- Economic Factor: Three questions regarding financial difficulties, such as housing costs, food, transportation, and overall daily living and education expenses.

To evaluate the APrISE-15 Dropout Tool, first, Confirmatory Factor Analysis (CFA) was applied to assess its factorial validity [31,32], to determine the model's fit [33] and to confirm the structural integrity of the instrument within the Greek educational context [34]. Next, Item Response Theory (IRT) was used to examine the overall performance of the APrISE-15 Tool [35,36], assessing item difficulty and discrimination [37] and each item's effective contribution to dropout risk assessment. Additionally, IRT complements the results of CFA and enhances the validity and adaptability of the instrument detecting Differential Item Functioning (DIF) [38] and allowing for adaptive testing [39].

To further establish the reliability and reinforce the validity of the APrISE-15 Dropout Tool, Cronbach's alpha [40] was calculated to assess internal consistency and to confirm meaningful item contribution, with a Cronbach's alpha more than 0.70 [41]. Additionally, by removing any item, if Cronbach's alpha increases, it indicates misalignment with the construct [42]. Finally, in the APrISE-15 Dropout Tool, positively worded items were reversed so that higher scores uniformly indicate a greater tendency toward dropout. On the other hand, items that are inherently negative did not need reversal, because they already reflect a higher probability of dropout when participants agree. As a result, 13 items were reversed and only 2 were retained in their original form to maintain their intended directionality.

In addition to the APrISE-15 Tool, the research questionnaire includes student burnout factors [26,27], student engagement factors [28], HADS factors [29,30], and students' frequency of participation in social activities and in on-line activities.

2.1 The Burnout Assessment Tool (GR-BAT-12)

The Burnout Assessment Tool-12 [26,27] is an instrument designed to measure student burnout, adapted for the academic context. It is a shortened version of BAT and includes 12 questions that assess 4 main axes: exhaustion, mental distance, emotional impairment and cognitive impairment. Each axis is measured using a Likert Scale, with higher scores indicating a greater risk of burnout. The 4 dimensions of BAT are directly related to the personal factor of the APrISE-15 Tool, which includes feelings of frustration, mental exhaustion and thoughts of dropping out of university. The BAT-12 has been validated for students, taking into account factors related to academic stress. The use of the BAT in research studies is very useful as it is reliable, it is not complex, and it contributes to the identification of symptoms and the appropriate implementation of interventions.

2.2 The Utrecht Work Engagement Scale (UWES-9) Tool

The Utrecht Work Engagement Tool, student version, is a validated instrument that measures work engagement and at the same time, it can be applied into the academic context, since students face similar challenges. It consists of 9 questions that assess 3 main axes: Vigor, Dedication, and Absorption, each rated on a Likert Scale from 0-Never to 6-Always. The total score is calculated as the average of the responses with higher values indicating strong work engagement. The scale is widely used in organizational studies, due to its short and reliable format, [28].

2.3 The Hospital Anxiety and Depression Scale (HADS) Tool

The Hospital Anxiety and Depression Scale tool [29,30] is an easy-to-use screening instrument designed to detect symptoms of anxiety and depression in non-psychiatric populations. It consists of 14 questions divided into 2 subscales: HADS-A with 7 anxiety questions and HADS-D with 7 depression questions. Each question is scored on a scale of 0-3, depending on the frequency or intensity of the symptom, with a total possible score of 0-21 per subscale. The use of the tool allows for the separation of stress that stems from chronic psychological burden and may lead to burnout, from that stemming from external, contextual factors, such as financial difficulties or academic demands, and lead to dropout. The HADS

has been internationally validated and is widely used in research studies providing a quick and reliable assessment, without focusing on physical symptoms, which may be influenced by other conditions [30].

2.4 Participants and Data collection

The sample of the present study consists of students from all the departments of Patras University. The research conducted using the APrISE-15 Dropout Tool lasted from November to December 2023 and was carried out in person, with 3,099 students completing the questionnaires. Missing values at the question level were minimal. Small variations in the actual sample size between analyses arose due to the use of composite indicators based on multiple questions. For IRT analyses, listwise deletion was applied, excluding cases with missing responses to any relevant question. In correlational analyses, Pearson coefficients were calculated with pairwise complete observations. All analyses were performed in R [43], with a statistical significance level of $p < 0.05$.

Table 1. Frequency and Percentage Distribution by Variable

Values	Frequency	Percentage	Cumulative Percentage
Sex			
Male	1313	42,49	42,49
Female	1762	57,02	99,51
	15	0,49	100,00
Year			
1st Year	1314	42,52	42,52
2nd Year	342	11,07	53,59
3rd Year	718	23,24	76,83
4th Year	481	15,57	92,40
5th Year	91	2,94	95,34
Extended Studies	144	4,66	100,00
Locality (The high school graduation and university are in the same region)			
Same Region	752	24,34	24,34
Different Region	2337	75,63	99,97
School			
	1	0,03	100
Agricultural Sciences	129	4,17	4,17
Economics and Business Administration	529	17,12	21,29
Engineering	913	29,55	50,84
Health Rehabilitation Sciences	401	12,98	63,82
Health Sciences	126	4,08	67,90
Humanities and Social Sciences	481	15,57	83,47
Natural Sciences	511	16,54	100,01

The demographic data of the sample, Table 1, are summarized across four key variables: locality, school, sex and year of study. In particular, (1) the majority of the participants (75.63%) are from regions different from the study area, while 24.34% are from the same region, (2) Engineering students make up the largest group (29.55%), followed by students in Economics and Business Administration (17.12%) and Humanities and Social Sciences (15.57%), (3) the 57.02% of the participants are female while the 42.49% are male and (4) the largest proportion of participants are in the first year (42.52%), followed by those in the third year (23.24%).

3. RESULTS

For the statistical analysis of the data, the R software was utilized, and the classical scores were calculated based on the mean of the responses derived from the corresponding items on the 1 to 7 Likert scale. In contrast, the IRT scores were computed using the probability density function of the parameter θ, reflecting the likelihood of a given value for each factor in the model.

3.1 Descriptive Statistics

The descriptive statistics for the Likert-scale variables, presented in Table 2, provide information on the central tendency, dispersion, and distributional properties of the factors related to drop out. The mean values indicate that Social (M = 4.33, SD = 1.20) and Institutional (M = 3.76, SD = 1.27) factors are rated higher, suggesting that they may play a more important role in the considerations of students' attrition, while Personal (M = 2.40, SD = 1.14) and Economic (M = 2.80, SD = 1.37) factors have lower means, indicating a smaller perceived impact. The skewness and kurtosis values reveal that most variables are approximately symmetrical. Although Personal (skew = 1.10, kurtosis = 0.99) and Economic (skew = 0.74, kurtosis = 0.06) exhibit a more right-skewed distribution, indicating a concentration of responses at the lower end of the scale. Overall, these descriptive statistics highlight the relative importance and distributional characteristics of different dropout factors, which must be further examined using inferential analyses.

Table 2. Descriptive Statistics for Items

Variable	vars	n	mean	sd	median	min	max	range	skew	kurtosis	se
Dropout	1	3089	3.329	0.823	3.267	1	6.933	5.933	0.390	0.412	0.015
Academic	2	3089	3.351	1.038	3.333	1	7.000	6.000	0.343	0.075	0.019
Aca01	3	3089	5.070	1.270	5.000	1	7.000	6.000	-0.786	0.455	0.023
Aca02	4	3086	4.473	1.501	5.000	1	7.000	6.000	-0.385	-0.372	0.027
Aca03	5	3082	4.403	1.420	4.000	1	7.000	6.000	-0.271	-0.341	0.026
Personal	6	3089	2.400	1.139	2.000	1	7.000	6.000	1.097	0.992	0.020
Pers01	7	3086	2.411	1.500	2.000	1	7.000	6.000	1.048	0.389	0.027
Pers02	8	3086	1.826	1.400	1.000	1	7.000	6.000	1.884	2.883	0.025
Pers03	9	3088	5.039	1.410	5.000	1	7.000	6.000	-0.700	0.162	0.025
Institutional	10	3089	3.762	1.275	3.667	1	7.000	6.000	0.194	-0.404	0.023
Inst01	11	3087	4.619	1.475	5.000	1	7.000	6.000	-0.515	-0.136	0.027
Inst02	12	3088	4.163	1.765	4.000	1	7.000	6.000	-0.152	-0.997	0.032
Inst03	13	3082	3.931	1.554	4.000	1	7.000	6.000	-0.096	-0.641	0.028
Social	14	3088	4.332	1.195	4.333	1	7.000	6.000	-0.218	-0.174	0.022
Soc01	15	3085	3.123	1.677	3.000	1	7.000	6.000	0.390	-0.845	0.030

Soc02	16	3085	2.611	1.619	2.000	1	7.000	6.000	0.812	-0.230	0.029
Soc03	17	3085	5.269	1.655	6.000	1	7.000	6.000	-1.084	0.476	0.030
Economic	18	3088	2.801	1.367	2.667	1	7.000	6.000	0.743	0.061	0.025
Eco01	19	3086	5.215	1.574	6.000	1	7.000	6.000	-0.801	-0.026	0.028
Eco02	20	3087	5.042	1.450	5.000	1	7.000	6.000	-0.670	-0.017	0.026
Eco03	21	3086	5.341	1.694	6.000	1	7.000	6.000	-0.912	-0.037	0.030

Next, in Table 3 are presented the descriptive statistics for the IRT-based scores of the APrISE-15 Tool, which were transformed using IRT and scaled to a 0-100 range. This transformation lets IRT estimate the dropout tendency independently of the scale or the tool used. Also, using the probability density function, the resulting scores become more interpretable and comparable across different samples and different IRT-based instruments. Consequently, the findings of this study can be directly compared with those of other studies using IRT-based tools to measure dropout tendencies, enhancing the generalizability and the robustness of the results.

The overall Dropout.irt score has a mean of 53.14 (SD = 19.46), indicating a moderate tendency toward dropout across the sample. Among the dimensions, Personal.irt has the highest mean score (63.38, SD = 23.32), suggesting that personal factors, such as feelings of disappointment and exhaustion, contribute most significantly to dropout tendencies. In contrast, Institutional.irt has the lowest mean score (46.80, SD = 30.40), implying that institutional factors, such as university support and infrastructure, play a relatively smaller role in dropout intentions. The Academic.irt and Economic.irt dimensions show moderate means (53.40 and 52.00, respectively), while Social.irt has a mean of 50.08, indicating that social factors are neither strongly nor weakly associated with dropout tendencies. The skewness and kurtosis values for all dimensions are close to zero, suggesting that the distributions are relatively symmetric and do not deviate significantly from normality.

Table 3. Descriptive Statistics for IRT Scores (Theta)

	mean	sd	median	min	max	range	skew	kurtosis
Dropout.irt	53.138	19.461	53.4	9.2	98.8	89.6	0.045	-0.643
Academic.irt	53.400	24.184	52.0	8.0	100.0	92.0	0.096	-1.027
Personal.irt	63.384	23.319	64.0	29.0	100.0	71.0	0.109	-1.344
Institutional.irt	46.802	30.396	44.0	1.0	98.0	97.0	0.116	-1.332
Social.irt	50.077	38.405	49.0	0.0	97.0	97.0	-0.044	-1.673
Economic.irt	51.996	34.202	47.0	8.0	100.0	92.0	0.109	-1.585

The correlation coefficients between the dropout-related factors are presented in Table 4 for both raw data and IRT-derived scores. The strong correlation between Dropout and Dropout.irt (r = 0.95) confirms that both classical and IRT-based approaches capture similar constructs. Likewise, the high correlations within each method (e.g., Academic and Academic.irt, r = 0.97; Institutional and Institutional.irt, r = 0.97) suggest that the factor structures are stable across the two measurement techniques. Examining the relationships between factors, dropout is most strongly associated with Academic (r = 0.70) and Institutional (r = 0.70), suggesting that academic and institutional challenges are key contributors to dropout risk. Personal factors correlate moderately with Dropout (r = 0.60), indicating a notable but slightly weaker effect. In contrast, Social (r = 0.48) and Economic (r = 0.61)

factors show weaker associations, implying that while they may influence dropout risk, they are not as dominant.

Table 4. Correlations Between Raw Scores and IRT Scores

	Dropout.irt	Academic.irt	Personal.irt	Institutional.irt	Social.irt	Economical.irt
Dropout	0.955	0.716	0.637	0.697	0.484	0.613
Academic	0.701	0.970	0.448	0.419	0.328	0.263
Personal	0.603	0.480	0.929	0.302	0.162	0.292
Institutional	0.701	0.418	0.319	0.972	0.260	0.327
Social	0.624	0.372	0.213	0.285	0.831	0.181
Economical	0.638	0.303	0.318	0.372	0.103	0.939

The cutoffs for both raw scores and IRT scores are calculated, Table 5, to categorize dropout risk into Low Risk, Moderate Risk, and High Risk. This categorization is based on the distribution of scores for each factor and their corresponding IRT scores. For raw scores, the 25th percentile (Q1) and 75th percentile (Q3) are calculated, and these percentiles are used to establish the risk boundaries: Low Risk is assigned to scores ≤ Q1, Moderate Risk to scores between Q1 and Q3, and High Risk to scores ≥ Q3. By using these clearly defined thresholds, we can more accurately identify students at different levels of risk, making the process of dropout prevention and intervention more focused and efficient.

Table 5. Calibration Table for Dropout Risk Factors

Factor	Low Risk (Raw)	Low Risk (f(θ))	Moderate Risk (Raw)	Moderate Risk (f(θ))	High Risk (Raw)	High Risk (f(θ))
Dropout	≤ 2.73	f(θ) < 38.6	2.73–3.8	38.6 ≤ f(θ) ≤ 67	≥ 3.8	f(θ) > 67
Academic	≤ 2.67	f(θ) < 34	2.67–4	34 ≤ f(θ) ≤ 73	≥ 4	f(θ) > 73
Personal	≤ 1.67	f(θ) < 44	1.67–3	44 ≤ f(θ) ≤ 86	≥ 3	f(θ) > 86
Institutional	≤ 3	f(θ) < 19	3–4.67	19 ≤ f(θ) ≤ 75	≥ 4.67	f(θ) > 75
Social	≤ 3.62	f(θ) < 10	3.62–5	10 ≤ f(θ) ≤ 92	≥ 5	f(θ) > 92
Economic	≤ 1.67	f(θ) < 18	1.67–3.67	18 ≤ f(θ) ≤ 89	≥ 3.67	f(θ) > 89

3.2 Confirmatory Factor Analysis (CFA)

A confirmatory factor analysis was applied to examine the factorial validity of the APrISE-15 Tool and the model's goodness-of-fit was assessed through multiple SEM fit indices, summarized as follows:

- Chi-Square Test (χ^2): $\chi^2 = 871.369$, df = 70, $p < 0.001$. While the significant p-value suggests the model does not perfectly fit the data, this result is expected in large samples (n > 200) and should be interpreted alongside other fit indices.
- Comparative Fit Index (CFI): 0.943. This value exceeds the recommended threshold of 0.90, indicating that the model accounts for a substantial proportion of the covariance in the data.
- Tucker-Lewis Index (TLI): 0.915. Also, above the 0.90 threshold, this suggests a robust model fit while penalizing complexity, making it a reliable fit indicator.

- Standardized Root Mean Square Residual (SRMR): 0.048. Below the 0.08 threshold, this indicates minimal residual covariance and a strong model fit.
- Root Mean Square Error of Approximation (RMSEA): 0.061 (90% CI: 0.058–0.065). While slightly above the ideal threshold of 0.06, it remains within the acceptable range (< 0.08). The narrow confidence interval underscores the estimate's precision.

Overall, these results support the validity of the five-factor structure of the APrISE-15 Dropout Tool, confirming its applicability for assessing dropout risk in the Greek educational context.

Below, in figure 1, the structural equation model diagram with the standardized factor loadings from the SEM analysis are presented.

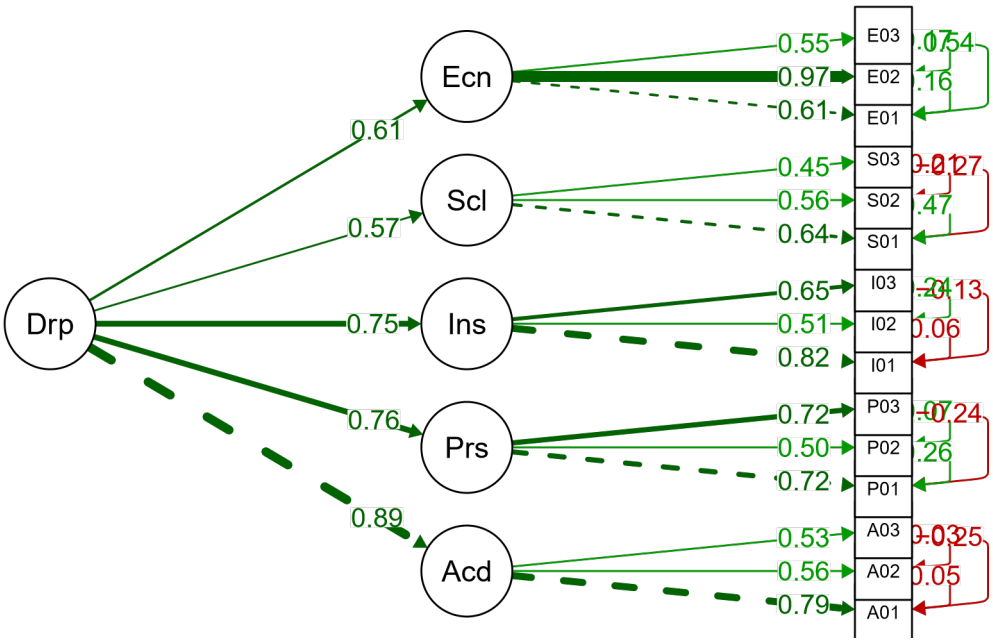

Fig. 1. Structural Equation Model (SEM) Diagram

All factor loadings were statistically significant ($p < 0.05$) and demonstrated strong relationships between the observed variables and their corresponding latent constructs. Academic factors, consist of Aca01= 0.793, Aca02= 0.563, Aca03= 0.529, show that the items effectively capture academic influences on dropout risk. Personal factors, consist of Pers01= 0.715, Pers02 = 0.504, Pers03 =0.721, indicate a particularly strong role within this dimension. Institutional factors, consist of Inst01 = 0.816, Inst02 = 0.513 and Inst03 =0.653, highlight the significance of institutional aspects in explaining dropout tendencies. Social factors, consist of Soc01 =0.638, Soc02 =0.558, and Soc03 = 0.453, demonstrate statistical significance ($p = 0.024$) and contribute to social influences and, finally, economic factors, consist of Eco01 =0.612, Eco02 = 0.969, underline the notable role of economic aspects. Finally, the standardized factor loadings for the five latent dimensions, Academic =0.889, Personal = 0.760, Institutional = 0.754, Social = 0.575 and Economic = 0.613, illustrate their relative contributions on the dropout factor. Highlighting the important role of academic factors in the dropout construct, followed by personal and institutional dimensions.

In addition to CFA, the analysis using Item Response Theory for the APrISE-15 Dropout Tool demonstrates that all factors show positive discrimination. This means that the items are designed to effectively identify students at varying levels of dropout risk.

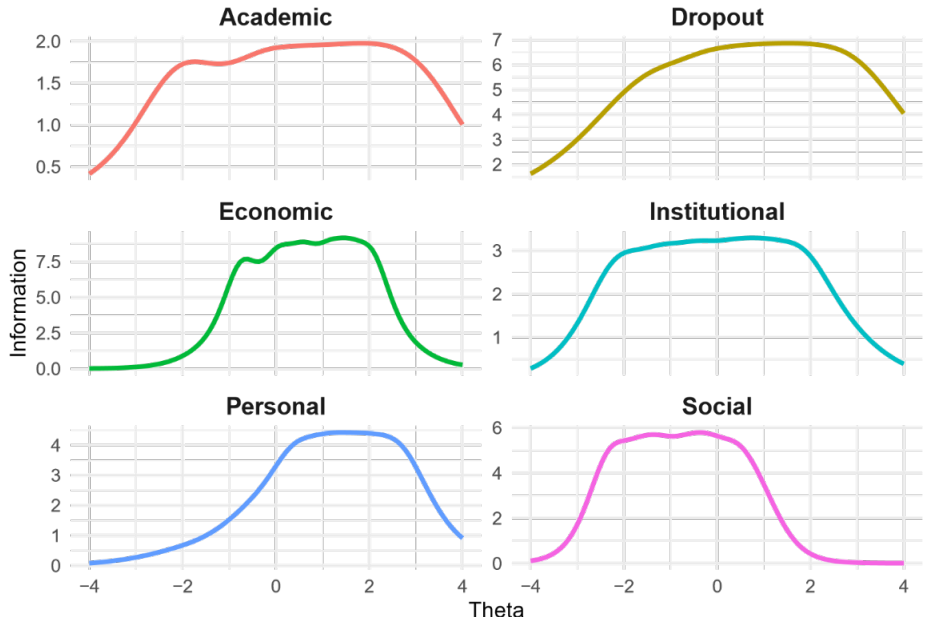

Fig. 2. IRT Information Curves by Factor

In Figure 2 are presented Item Response Theory (IRT) information curves for the five factors - Academic, Personal, Institutional, Social, Economic- that influence students´ dropout intentions. Each panel displays the information curves for a specific factor, illustrating how effectively the items measure the latent trait (Theta) across different ability levels. The curves peak at moderate Theta values, indicating that the items are most informative for students with moderate levels of dissatisfaction or disengagement. The figure highlights the discriminative power of the items within each factor, providing insights into their utility for identifying students at risk.

The reliability analysis of the APrISE-15 Tool yielded strong internal consistency, with a raw alpha of 0.822, a standardized alpha (std.alpha) of 0.827, and an average inter-item correlation (average_r) of 0.242. The asymptotic standard error (ase) was low at 0.005, suggesting precise estimates, the mean score was 3.329 and the standard deviation (sd) was 0.823, reflecting the central tendency and the variability of responses. In general, the findings confirm the tool's robustness for measuring student dropout tendencies.

Below, in Table 6, is described the reliability of the APrISE-15 Dropout Tool if each individual item is removed. The results reveal that the tool maintains strong internal consistency, with raw alpha values ranging from 0.800 to 0.825.

Table 6. Reliability if an Item is Dropped

Item	raw_alpha	std_alpha	G6_smc	average_r	S_N	alpha_se	var_r	med_r
Aca01	0.805	0.809	0.842	0.232	4.223	0.005	0.018	0.210
Aca02	0.813	0.818	0.851	0.243	4.498	0.005	0.019	0.214
Aca03	0.815	0.820	0.854	0.246	4.569	0.005	0.019	0.217
Pers01	0.811	0.815	0.845	0.240	4.413	0.005	0.017	0.221
Pers02	0.816	0.821	0.850	0.247	4.598	0.005	0.017	0.225
Pers03	0.809	0.814	0.847	0.238	4.380	0.005	0.019	0.217
Inst01	0.804	0.809	0.843	0.232	4.238	0.005	0.018	0.205

Inst02	0.816	0.821	0.851	0.246	4.574	0.005	0.018	0.226
Inst03	0.807	0.813	0.844	0.237	4.345	0.005	0.018	0.211
Soc01	0.816	0.821	0.845	0.247	4.590	0.005	0.017	0.225
Soc02	0.818	0.824	0.847	0.250	4.676	0.005	0.016	0.234
Soc03	0.825	0.829	0.861	0.258	4.861	0.005	0.018	0.234
Eco01	0.810	0.816	0.841	0.240	4.432	0.005	0.015	0.217
Eco02	0.800	0.806	0.837	0.228	4.146	0.005	0.016	0.210
Eco03	0.813	0.818	0.845	0.243	4.503	0.005	0.015	0.226

3.3 Internal consistency (Cronbach's alpha)

Cronbach's alpha values for the APrISE-15 Dropout Tool provide insights into the internal consistency of the instrument across its five factors (Academic, Personal, Institutional, Social, and Economic) and the full scale. In particular, the academic factor has an a=0.589, the personal factor has an a =0.703, the institutional factor has an a=0.710, the social factor has an a=0.547 and the economic factor has an a=0.835. The personal, institutional and economic factors with alpha values above the 0.70 threshold, indicate that perform adequately for the purpose of the tool, are highly reliable and consistently measure the same construct. The academic and the social factors, even though present values lower than 0.70, also are considered suitable for the tool, because for items fewer than 10, an alpha value above 0.50 is considered acceptable [44]. As a result, these alpha values are within the acceptable range. Finally, the full scale demonstrates excellent internal consistency, with an alpha value of 0.822, confirming that the APrISE-15 tool reliably measures the construct of dropout risk.

3.4 Relationships between dropout risk and burnout, engagement, anxiety/depression.

The correlation analysis between the dropout phenomenon, academic burnout, academic engagement and anxiety/depression reveals several significant relationships among academic, economic, psychological and mental health factors. To begin with, dropout seems to have positive correlation with burnout (0.48), anxiety (0.27) and depression (0.36), indicating that increases emotional exhaustion, mental detachment, reduced effectiveness, high levels of stress, emotional distress and loss of motivation are serious predictors of dropout. However, a negative correlation was recorded between dropout and engagement (-0.59), indicating that the more students are active and enthusiastic about their studies, the lower the likelihood of leaving university.

In a similar vein, dropout rates seem to have a strong positive correlation with academic and institutional related variables, such as Acad (0.73), Pers (0.67), and Inst (0.73), indicating that students who feel disengagement in academic and institutional contexts are more likely to abandon their studies. This underscores the critical influence of academic dissatisfaction and insufficient institutional support on student retention. Economic factors also have a key role, with a moderate positive correlation to Econ (0.68), suggesting that financial stress and economic instability are important contributors to dropout tendency. Consistent with this argument, burnout and exhaustion increase dropout rates, as evidenced by the positive relationships with Burnout (0.48) and Exh (0.31), highlighting the importance of addressing both mental and physical fatigue. Similarly, mental and cognitive impairments show positive correlations, with MentDist (0.49) and CogImp (0.35) indicating that psychological strain and cognitive challenges undermine students' ability to persist in their studies.

On the other hand, negative correlations uncover protective factors against dropout. To begin with, academic engagement is strongly negatively correlated (-0.59) with dropout, indicating that greater commitment and motivation can decrease the likelihood of students leaving university. Furthermore, absorption, dedication and vigor show negative correlations, with Abs (-0.5), Ded (-0.57), and Vig (-0.5) highlighting the protective impact of emotional investment and active participation on the learning process.

3.4.1 Bifactor model of dropout and burnout analysis

In order to better understand the relationship between academic burnout and dropout, it was deemed appropriate to use the bifactor model which allows for the coexistence of a general factor and individual specific factors in a single structure. Figure 3 illustrates the structure of the bifactor model, where the observed variables load simultaneously on both the general and the corresponding specific factor. The general factor captures the common variance of all indicators, while the specific factors reflect the unique contribution of each subdimension (student dropout and academic burnout), after removing the impact of the general factor. The model was estimated using the Maximum Likelihood Method (ML) with all parameters being statistically significant (p<0,001).

The bifactor model shows that the general factor influences almost all indicators with stronger effect mainly on personal (0.90) and secondarily on academic (0.59) dimensions. However, the specific factors, dropout and burnout, additionally influence specific variables, such as burnout~ exhaustion (0.46) and dropout ~institutional (0.54) and dropout~ social (0.40). Also, observing the figure, it appears that the loadings of dropout are smaller compared to those of burnout, something expected and normal given that dropout is a more multifactorial phenomenon.

The correlation between dropout and burnout indicates a strong positive relationship between the two constructs, as a result higher levels of student burnout are associated with increased students´ dropout tendency. Overall, the bifactor model confirms the existence of a general factor that influences both dropout and burnout and at the same time, maintains the uniqueness of the two specific factors. Finally, the strong correlation between burnout and dropout highlights the need for a holistic approach to addressing these phenomena.

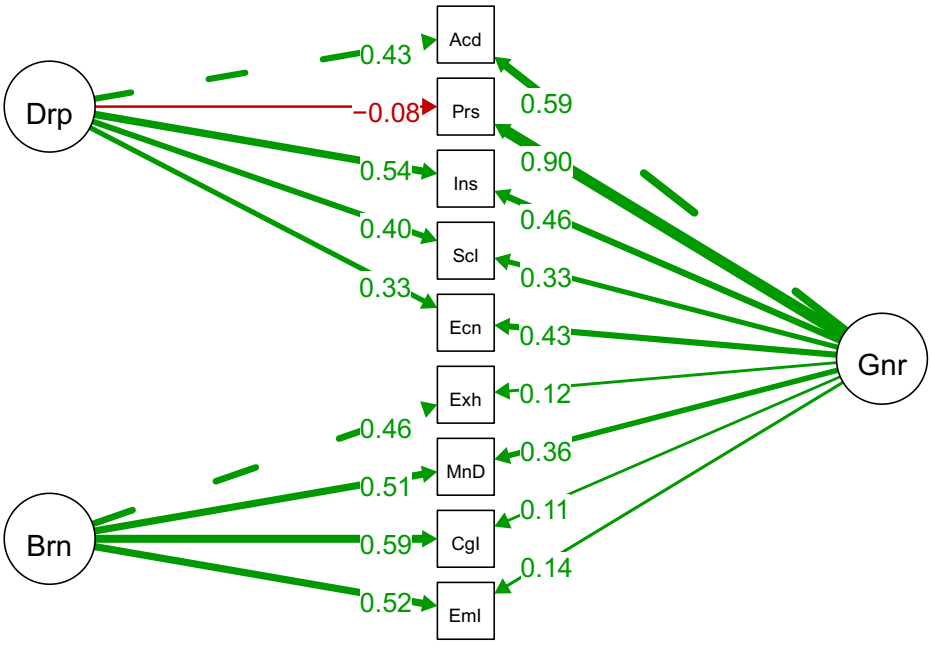

Fig. 3. Bifactor model of dropout and burnout analysis

3.5 Demographic Variations

The results, in Table 7, indicate that significant gender differences were observed for the Academic and Personal dimensions, where males tend to report higher levels of dropout. On the other hand, no significant gender differences were observed for the Institutional, Social, and Economic dimensions, indicating that these factors may be less influenced by gender in the sample of this study.

Table 7. Differences of Dropout with Sex

Variable	t-statistic	df	p-value	Mean (Male)	Mean (Female)	95% CI Lower	95% CI Upper
Dropout	2.494	2737.068	0.013	3.371	3.296	0.016	0.135
Academic	2.455	2800.725	0.014	3.404	3.311	0.019	0.168
Personal	4.570	2718.426	<0.001	2.512	2.321	0.109	0.273
Institutional	1.046	2783.383	0.296	3.787	3.739	-0.043	0.140
Social	1.439	2711.130	0.15	4.366	4.303	-0.023	0.150
Economic	-0.316	2837.521	0.752	2.792	2.807	-0.113	0.082

As far as the academic year is concerned, the analysis reveals that students in extended studies and in the third year have significantly higher dropout scores (p-value < 0.01), while students in the 4th year have significantly lower dropout scores compared to third year and compared to extended year (p-values < 0.01). Furthermore, based on the results of the Welch Two Sample t-test (p-value= 0.3810873), it is obvious that there is no significant difference in dropout tendency between students from the same region and those from a different region. However, according to the Dunn's test results, there are significant differences in dropout tendencies among schools, with students in Health Rehabilitation Sciences to be less likely to drop out.

4. DISCUSSION

The aim of this study was to assess the APrISE-15 Dropout Tool for use in the Greek educational context. The findings from the study support the ad hoc instrument as a valid and reliable measure for assessing dropout risk among students. The tool's strong internal consistency and good model fit indicate that it effectively captures the multifaceted nature of dropout phenomenon. This multidimensional assessment provides a comprehensive view of the causes driving dropout and their crucial role in predicting dropout. According to the findings of the present study, burnout and financial stress are consistently associated with higher dropout rates. Burnout results from academic stress, exhaustion, and emotional disengagement, and all these negative factors increase the likelihood of dropout. High engagement, absorption, and emotional resilience are protective factors, while burnout, exhaustion, and mental health issues exacerbate the risk of dropout.

During the process of drafting the tool, a selective approach was followed in order to reduce the number of questions per factor from 69 [2,3] to 15, maintaining those that reflect, in the most representative way, the content of each conceptual axis. As a result, based on thematic relevance, internal coherence, theoretical weight and discernment, in the academic factor were retained the items that combine subjective satisfaction with the perceived value and the effectiveness of education and in the personal factor were rejected the items that presented thematic repetition and did not resemble a personal phycological state. Similarly, in the institutional factor the selected questions cover critical aspects of the institutional role of the university, in the social factor were rejected the items that were deemed not to adequately capture the essence of social interactions oriented towards the content of studies and finally, in the economic factor were reserved the items that focus on basic and necessary economic dimensions that decisively affect the ability to attend university.

In the same line of argument, in the present study it was decided to maintain an equal number of items per factor because the uniformity ensures balanced participation of all thematic areas, allows comparison among them on equal terms, makes the tool flexible for use in different cultural and institutional contexts and facilitates the use of cutoff scores to assess the impact of each factor. A fixed number of questions allows for easier constructions of indicators, standardization of results and maintenance of comparability among populations or samples from different environments. Finally, uniform weighting does not imply

equalizing the substantive influence of each factor, but is a conscious strategy to maintain balance, comparability and inter-applicability of the tool.

To sum up, the tool's applicability in the Greek educational context offers valuable insights for educators and policymakers, letting them pinpoint the areas that require interventions. The universities should address psychological, academic, institutional, and financial issues to mitigate dropout risk effectively. Interventions should focus on providing robust mental health support, academic mentoring, and financial aid to students who deal with academic burnout, financial stress, and anxiety. Addressing the root causes of disengagement, mental health issues, and of economic challenges can help in enhancing students' retention and in mitigating the dropout rates.

5. LIMITATIONS

Although the present study offers valuable insights into dropout risk, there are some limitations to consider. The sample was restricted to a single university, which may limit the generalizability of the findings to other Greek universities. However, Patras, as the third largest city in Greece, hosts students from various regions of the country. In particular, Patras University is regional, which means that the sample consists of a combination of local and distant students. This characteristic makes the sample representative of the geographical diversity of the country, with students from all over Greece, as the admission system in Greece is based on national exams, allowing entry to the University from every corner of Greece. In addition to this, the use of IRT ensures that the results are not influenced by the sample, allowing the objective assessment of the parameters at a global level. On the other hand, cutoffs may be affected by sample composition. The presence of local and distant students may lead to small differences in the minimum indicators recorded in the responses, which may have an impact on the interpretation of the results and comparisons between different parameters.

Moreover, the study's cross-sectional design restricts the understanding of the long-term effects of the five factors (academic, personal, institutional, social, economic) influencing dropout rates. For this reason, future research should conduct longitudinal studies to identify how these factors impact dropout over time. Additionally, the reliance on self-reported data introduces the potential for bias, as students may either underreport or overreport their experiences. While the sample size was large, it may not be fully representative of all populations. The study, also, did not take into account other variables, such as socioeconomic status or cultural background, which could play an important role in the dropout phenomenon.

6. CONCLUSION

The present study successfully adapts the APrISE-15 Dropout Tool to assess dropout risk among Greek students, demonstrating its utility as an instrument for the prevention of the dropout phenomenon. The validation of the tool, in line with its strong factor loadings and good model fit, confirms its effectiveness in identifying students at risk. Despite the limitations, the findings significantly contribute to understanding the root causes of dropout and highlight the importance of addressing its multiple dimensions. Future research should build on these findings by conducting longitudinal studies to explore the long-term effects of the five factors that have a significant impact on dropout risk. Expanding the research to include more Greek universities would improve the generalizability of the results and integrating qualitative methods, such as interviews, could offer deeper insights into the personal experiences of students and the underlying causes of dropout. Additionally, interventions aimed at enhancing students' retention should focus on students in Extended Studies and those in the third year, as these groups exhibit higher tendencies to drop out, according to the findings. Moreover, the results reveal the existence of significant differences in dropout rates across different faculties. For this reason, it is important to develop school-specific strategies to address dropout tendencies and improve student retention. Finally, broadening the research in other countries with the aim to observe how the APrISE - 15 Tool performs outside of the Greek educational context would be beneficial, as the dropout phenomenon is a challenge globally.

REFERENCES

[1] Alban, M. S & Mauricio, D 2019, ´ Predicting university dropout through data mining: A systematic literature review´, Indian Journal of Science and Technology, vol.12, no.4, < https://doi.org/10.17485/ijst/2019/v12i4/139729>.

[2] Androulakis, G. S., Georgiou, D. A., Kiprianos, P & Stamelos, G, 2020, ´Examining the sequence of factors affecting students' tendency to dropout: A case study in Greece´, International Journal of Education, vol.12, no.4, <https://doi.org/10.5296/ije.v12i4.17835>.

[3] Androulakis, G. S., Georgiou, D. A., Kiprianos, P & Stamelos, G 2021, ´The role of the academic factor in student's tendency to university dropout.´ Journal of Education and Human Development, vol.10, no.1, pp. 50-62, <https://doi.org/10.15640/jehd.v10n1a5 >.

[4] National Authority for Higher Education (ETHAAE) 2024, Annual Report 2023, viewed December 2024,< https://www.ethaae.gr/el/ethaae/etisies-ektheseis-ethaae>.

[5] Barefoot, B. O 2004, 'Higher education's revolving door: confronting the problem of student drop out in US colleges and universities', Open Learning: The Journal of Open, Distance and e-Learning, vol. 19, no. 1, pp. 9–18, <https://doi.org/10.1080/0268051042000177818>.

[6] Davidson, J. C. & Wilson, K. B 2016, 'Community college student dropouts from higher education: toward a comprehensive conceptual model', Community College Journal of Research and Practice, vol. 41, no. 8, pp. 517–530, <https://doi.org/10.1080/10668926.2016.1206490>.

[7] Díaz, P. & Tejedor De León, A 2016, 'Design and validation of a questionnaire to analyze university dropout—CADES', World Journal of Educational Research, vol.3, no.2, https://doi.org/10.22158/wjer.v3n2p267

[8] Hibbett, A. U 1986, 'Dropping out or staying on: characteristics of drop-out students and course completers', Studies in the Education of Adults, vol. 18, no. 2, pp. 71–81, <https://doi.org/10.1080/02660830.1986.11730468>.

[9] Koelsche, C. L 1956, 'A study of the student drop-out problem at Indiana University', The Journal of Educational Research, vol. 49, no. 5, pp. 357–364, <https://doi.org/10.1080/00220671.1956.10882294>.

[10] Stamelos, G., Kiprianos, P., Nikolaou, G. & Androulakis, G. S 2022, 'Student's personal coping with university studies while facing drop out', European Journal of Education and Pedagogy, <https://doi.org/10.24018/ejedu.2022.3.6.493>.

[11] Tinto, V 1975, ´Dropout from higher education: A theoretical synthesis of recent research´, Review of Educational Research, vol.45, no.1, pp. 89-125, <https://doi.org/10.3102%2F00346543045001089>.

[12] Krishnan, K., Venugopalan, M. & Sahib, P 2024, 'Tailoring success: ´How individualized learning and increased awareness can combat dropout in skill development programs´, Journal of Open Innovation: Technology, Market, and Complexity, vol.10, no.4, p. 100430, < https://doi.org/10.1016/j.joitmc.2024.100430>.

[13] Benito-Gomez, M., Lee, G. Y., McCurdy, A. L., & Fletcher, A. C 2022, '"If I hadn't had that support system, I think I would have dropped out by now": parental support in college and its implications for student adjustment', Journal of Family Issues, vol. 43, no. 12, pp. 3373–3394, < https://doi.org/10.1177/0192513X211044490>.

[14] van der Ploeg, N., Linden, K. & Teakel, S 2025, 'Nudge power in higher education: altering choice defaults to reduce student failure and associated debt', Journal of Higher Education Policy and Management, vol.47, no.3, p.317-334, <https://doi.org/10.1080/1360080X.2024.2446322>.

[15] van Zyl, A. & Blaauw, P 2012, 'An integrated project aimed at improving student success', Africa Education Review, vol. 9, no. 3, pp. 466–484, <https://doi.org/10.1080/18146627.2012.741342>.

[16] Petronela Cristina SIMION, Mirona Ana Maria POPESCU, Corina-Ionela DUMITRESCU, Iustina-Cristina COSTEA-MARCU 2024, "An intelligent platform for guiding future students to

optimal university programs", International Conference on Virtual Learning, ISSN 2971-9291, ISSN-L 1844-8933, vol. 19, pp. 283-297, < https://doi.org/10.58503/icvl-v19y202424>

[17] Osman**,** D., Janmani, Y., Phillips, M., Gittens, D. & Imo, T 2023, ´Forecasting student retention rates in accounting and business programs at historically black colleges and universities´, African Journal of Accounting, Economics, Finance and Banking Research, vol.16, no.16.

[18] Cross, J. D. & Carman, C. A 2021, 'The relationship between faculty diversity and student success in public community colleges', Community College Journal of Research and Practice, vol. 46, no. 12, pp. 855–868, <https://doi.org/10.1080/10668926.2021.1910595>.

[19] Marzuqi, T. A., Kristiani, E. & Marcel, M. 2024. ´Prediksi mahasiswa drop-out di Universitas XYZ. Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)´, vol.11, no.6, pp. 1345-1350, <https://doi.org/10.25126/jtiik.2024118689>.

[20] Griffin, S 2025,´ Predicting drop-out in Toastmasters´, Doctor of Education (EdD) thesis, The Open University, <https://doi.org/10.21954/ou.ro.00102495>.

[21] Nguyen Thi Cam, H., Sarlan, A., & Arshad, N. I 2024, ´A hybrid model integrating recurrent neural networks and the semi-supervised support vector machine for identification of early student dropout risk´, PeerJ Computer Science, vol.10,no.1, https://doi.org/10.7717/peerj-cs.2572.

[22] Kemper, L., Vorhoff, G. & Wigger, B. U 2020, 'Predicting student dropout: A machine learning approach', European Journal of Higher Education, vol. 10, no. 1, pp. 28–47, < https://doi.org/10.1080/21568235.2020.1718520>.

[23] Bulotaitė, L., Sargautytė, R., Žukauskaitė, I. and Bagdžiūnienė, D 2025, ´Study Environment and Psychological Factors of University Students' Intention to Drop out´. Acta Paedagogica Vilnensia, 53, pp. 89–105, https://doi.org/10.15388/ActPaed.2024.53.7

[24] Lerdpornkulrat, T., Koul, R. & Poondej, C 2018, 'Relationship between perceptions of classroom climate and institutional goal structures and student motivation, engagement and intention to persist in college', Journal of Further and Higher Education, vol. 42, no. 1, pp. 102–115, <https://doi.org/10.1080/0309877X.2016.1206855>.

[25] Cortes, K., Mostert, K. & Els, C 2014, 'Examining significant predictors of students' intention to drop out', Journal of Psychology in Africa, vol. 24, no. 2, pp. 179–185, <https://doi.org/10.1080/14330237.2014.903070>.

[26] Androulakis, G. S., Georgiou, D. A., Lainidi, O., Montgomery, A. & Schaufeli, W. B 2023, ´The Greek Burnout Assessment Tool: Examining its adaptation and validity´, International Journal of Environmental Research and Public Health, vol.20, no.10, pp. 5827, <https://doi.org/10.3390/ijerph20105827>.

[27] Schaufeli, W. B., De Witte, H. & Desart, S 2020, ´Manual Burnout Assessment Tool (BAT) – Version 2.0´, KU Leuven, Belgium: Unpublished internal report.

[28] Schaufeli, W. and Bakker, A. 2004, ´UWES Utrecht Work Engagement Scale Preliminary Manual´, Occupational Health Psychology Unit Utrecht University, Utrecht.

[29] Michopoulos, I., Douzenis, A., Kalkavoura, C., Christodoulou, C. Michalopoulou, P., Kalemi, G., Fineti, K.,Patapis, P., Protopapas, K., & Lykouras, L 2008,´ Hospital anxiety and depression scale (HADS): Validation in a Greek general hospital sample´, Ann Gen Psychiatry, vol.7, no.4, <doi: 10.1186/1744-859X-7-4>

.[30] Zigmond, A. S., & Snaith, R. P 1983,´ The Hospital Anxiety and Depression Scale´, Acta Psychiatrica Scandinavica, vol.67,no.6, pp.361-370, <https://doi.org/10.1111/j.1600-0447.1983.tb09716.x.>.

[31] Brown, T. A 2015, Confirmatory Factor Analysis for Applied Research, 2nd ed., Guilford Press.

[32] Kline, R. B 2016, Principles and Practice of Structural Equation Modeling, 4th ed., Guilford Press.

[33] Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A. & King, J 2006, 'Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review', The Journal of Educational Research, vol. 99, no. 6, pp. 323–338, https://doi.org/10.3200/JOER.99.6.323-338.

[34] Fornell, C. & Larcker, D. F 1981, 'Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics', Journal of Marketing Research, vol. 18, no. 3, pp. 382–388, https://doi.org/10.1177/002224378101800313.

[35] Embretson, S. E. & Reise, S. P 2000, Item Response Theory for Psychologists, Lawrence Erlbaum Associates, New York.

[36] van der Linden, W. J 2016, Handbook of Item Response Theory, CRC Press, New York.

[37] De Ayala, R. J. (2009). *The theory and practice of item response theory.* Guilford Press.

[38] Camilli, G. & Shepard, L. A 1994, Methods for Identifying Biased Test Items, SAGE Publications.

[39] van der Linden, W. J. & Glas, C. A. W 2010, Elements of Adaptive Testing, Springer.

[40] Cronbach, L. J 1951, 'Coefficient Alpha and the Internal Structure of Tests', Psychometrika, vol. 16, no. 3, pp. 297–334, https://doi.org/10.1007/BF02310555.

[41] Nunnally, J. C. & Bernstein, I. H 1994, Psychometric Theory, 3rd ed., McGraw-Hill, New York.

[42] Pallant, J. (2020). SPSS Survival Manual: A Step by Step Guide to Data Analysis Using IBM SPSS. London: McGraw-Hill, Open University Press. https://doi.org/10.4324/9781003117452

[43] R Core Team 2024 R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. < https://www.R-project.org/>.

[44] Pallant, J 2010, SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS, Open University Press/McGraw-Hill, Maidenhead.

[45] GitHub, APrISE-15 Dropout Tool Data and Supplementary Material, GitHub Repository., <https://github.com/gandroul/APrISE >.