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Structural Analysis of the Academic Motivation Scale (Spanish version) in Graduate Students

Análisis Estructural de la Escala de Motivación Educacional (versión en español) en Estudiantes Graduados

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Abstract

This research aimed to examine the factor structure of the Academic Motivation Scale (AMS) in master's and doctoral students from universities in Puerto Rico; 300 students between 21 to 40 years (M = 29.14; SD = 4.87) participated. Confirmatory factor analysis, internal consistency, correlation, and item analysis were performed. Results of the current study provide evidence that supports the internal structure of the AMS and the ancillary statistics use of the bifactor model presents some interesting information about the possible unidimensional or multidimensional uses of the AMS. The subscales of the AMS obtained good reliability coefficients, and the AMS appears to be invariant among gender and age, which permits comparison among these groups. The use of the AMS appears useful in the educational context with graduate students in Puerto Rico. The implications and limitations of the findings are discussed.

Keywords: *academic motivation, extrinsic motivation, intrinsic motivation, graduate students, psychometrics*

Resumen

Esta investigación se propuso examinar la estructura factorial de la Escala de Motivación Académica (EMA) en estudiantes de maestría y doctorado de universidades de Puerto Rico. Participaron 300 estudiantes con edades que fluctuaron entre 21 a 40 años (M = 29.14; SD = 4.87). Se realizaron análisis factoriales confirmatorios, análisis de consistencia interna, análisis de correlación y análisis de ítems. Los resultados aportan pruebas que respaldan la estructura interna de la EMA y el uso estadístico auxiliar del modelo bifactorial presenta alguna información interesante sobre los posibles usos unidimensionales o multidimensionales de la EMA. Las subescalas de la EMA obtuvieron buenos coeficientes de fiabilidad y la EMA parece ser invariante entre el género y la edad, lo que permite realizar comparaciones entre estos grupos. El uso de la EMA parece ser útil en el contexto educativo con estudiantes graduados en Puerto Rico. Se discuten las implicancias y limitaciones de los hallazgos.

Palabras clave: *motivación académica, motivación extrínseca, motivación intrínseca, estudiantes graduados, propiedades psicométricas*

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Introduction

The guidance that university students receive from their professors has become a dynamic process that includes academic, personal, and professional areas; individually oriented to encourage students to create their way of working as independent professionals (Rodríguez et al., 2009). In the search to know the importance and the impact on the motivational variables in the academic performance, the literature reflects that self-efficacy strategies contribute to academic performance, organization, understanding and support strategies, and goals in learning (Becerra-González & Reidl-Martínez., 2015). This same author mentions that students with good academic performance recognize that the skills of the teacher and the didactic strategies for the development of the curriculum and institutional policies are not determining factors in academic performance. However, school performance, academic attributional style, motivation to school achievement, and academic self-efficacy have been related as determining factors (Becerra-González & Reidl-Martínez, 2015). Gutiérrez mentions that no statistically significant differences have been found between students' academic performance, intrinsic motivation, and self-efficacy. Nevertheless, positive correlations were found between cognitive strategies and subfactors of self-efficacy in general and motivation (Gutiérrez-Ruiz, 2015).

Motivation is one of the variables most frequently studied in the educational area and is also known as a multidimensional construct (Guzmán et al., 2006). It defines the internal and external components that promote the appearance of some behaviors (Candela et al., 2014). Moving to the educational area and considering the behavior of the human being, it is indisputable that the attitudes, perceptions, expectations, and ideas that the student has of himself, of the fulfillment of subjects, and of the objectives that he wishes to fulfill compose factors that offer direction. They lead student behavior in the school area. In any case, the external variables that come from the context in which the students operate must be considered, which is an aspect that influences them (Sánchez & Hernández-Pina, 2011).

Motivation has two variants: intrinsic motivation and extrinsic motivation; in teaching settings, emphasis is placed on differentiating one from the other on many occasions. Intrinsic motivation is related to behaviors for the interest of the activity itself, thinking only about its end and not as a way to achieve goals. Moreover, intrinsic motivation arises in people who are interested in learning, knowing and explaining phenomena. How obstacles are overcome is one of the most critical aspects of intrinsic motivation and is connected to the learning approach and competitive self-improvement of a high level of performance (Román-Pérez, 2013). On the other hand, extrinsic motivation is considered when the person performs an activity to satisfy other reasons unrelated to the activity itself (Ruiz, 2015). Motivation is an aspect that induces the way people think, and as a result, learning is affected (Alonso-Tapia, 1998). A student who performs activities out of interest, intrinsically motivated, is more receptive to make significant mental efforts while performing the activity, by using effective learning strategies (Lepper, 1988).

Unlike intrinsic motivation, extrinsic motivation leads to the accomplishment of the task with external aspects. The emotions that arise from the extrinsically motivated person occur through the expected results after performing the task (Sánchez & Hernández-Pina, 2011). In the educational area, Skinner justified using reinforcement and recognizing appropriate behavior; he understood that these strategies were more effective than applying punishment to modify the behavior to be achieved. Over the years, studies on learning continued, and it was shown that applying reinforcement and recognition promotes superficial learning in which students perform tasks without showing genuine interest. The objective of performing them was to avoid punishment or receive some positive reinforcement (Sánchez & Hernández-Pina, 2011). This suggests that there is a possibility that the student, who is motivated in an extrinsic way, shows commitment in the academic area only when they have the opportunity of some reward. They are likely in search of more straightforward tasks to ensure success rewards (Lepper, 1988).

As found in the literature, in a study on the sense of self-efficacy in graduate students, it turned out that intrinsic motivation was the most influential personal factor in self-efficacy to complete master's studies (Reyes-Cruz & Gutiérrez-Arceo, 2015). On the other hand, in an investigation of self-regulation in university students: learning strategies, motivation, and emotions, which aimed to evaluate emotional incidents and motivational beliefs according to the results of the tasks performed, it turned out that significant differences were found depending on the emotion and subjective competence beliefs used by the student. Another component of motivation is amotivation. This is considered the lowest level of autonomy in the different types of motivation; it is identified when the person does not perceive causality between the behavior and the consequences and does not feel competent in obtaining the desired goal (Deci & Ryan, 2000).

Theoretical framework

The theory of self-determination tells us that in order to achieve a better understanding of human motivation; it is necessary to consider the innate psychological needs of individuals for competence, autonomy and relationships. These needs are necessary for continued psychological growth, integrity, and well-being (Zhang et al., 2005). These authors establish that human needs indicate the necessary conditions for psychological well-being, and therefore, their satisfaction could be associated with satisfactory levels of motivation. Satisfaction of the three needs is necessary since it has been shown that it is not enough to satisfy some of them. By satisfying these innate needs, intrinsic motivation is maintained or improved, while the internalization and integration of extrinsic motivation are facilitated. On the contrary, some of the frustrated satisfaction can be reflected in unfavorable functions towards persistence and performance. In addition, it is associated with less intrinsic motivation and more intense extrinsic aspirations, which impact experiences, performance, and decreased well-being (Zhang et al., 2005).

Academic Motivation Scale

The Academic Motivation Scale, validated by Núñez et al. (2010), was used to review and validate it, including the integrated regulation to measure motivation in initial teacher training (Burgueño et al., 2017). A study to discover the motivational profiles of studying medicine was accomplished. This study was completed in 3 universities in Ecuador (Chicaiza-Ayala & Cragno, 2018), while in Brazil, a study in which integrated regulation was added to the Educational Motivational Scale was performed, and the psychometric properties were observed (Silva et al., 2018). On the other hand, Núñez et al. in 2010 carried out an adaptation and validation of the version of the Academic Motivation Scale in post-compulsory secondary education students.

After identifying that the instruments for analyzing the types of motivation within the self-determination variable were limited, Vallerand et al. (1993) developed and validated *Echelle de Motivation en Education* in French. This instrument is designed with 28 items and, in turn, divided into seven subscales of four items. This scale is subdivided into three areas of motivation: extrinsic, intrinsic and amotivation. This validation study had satisfactory levels of internal consistency, with a Cronbach's alpha of .80. Later this scale was translated into English and resulted in the Academic Motivation Scale (AMS). This procedure was carried out with a sample of students from Canada. The validation study results yielded a Cronbach's alpha of .62 and .86, reflecting good internal consistency. Later, another study was performed and good levels of construct validity were obtained in the correlation analysis between the seven subscales (Vallerand et al., 1993).

However, the scale was translated into Spanish and subjected to psychometric analysis by Núñez et al. (2010). The AMS is made up of 28 self-report items that answer the question *Why are you going to university?* with Likert-type responses ranging from *Does not correspond at all* (1) to *totally corresponds* (7), with an intermediate score, *It corresponds moderately* (4). Some of the questions say: *Because for me it is a pleasure and satisfaction to learn new things; I don't know why I'm going to college and, frankly, I don't care*; and *Because I want to show myself that I am capable of succeeding in my studies*. The scale has internal consistency in its seven subscales (Amotivation, External Regulation, Introjected Regulation, Identified Regulation, Intrinsic Motivation to knowledge, Intrinsic Motivation to achievement and Intrinsic Motivation to stimulating experiences) with values between .76 and .84, except in the Regulation subscale identified with .67.

Research Purpose

This study aims to validate and adopt the Academic Motivation Scale (AMS) in Puerto Rico. At the moment, in Puerto Rico, no scale measures academic motivation. The AMS was initially validated in French (Vallerand, 1993) with a Cronbach alpha .80, then in English (Vallerand et al., 1992) with a Cronbach alpha .62 and .86, and finally in Spanish (Núñez et al., 2010) with a Cronbach alpha between. 67 and .84. In the studies that have been carried out previously, this instrument has proven to be adequate to evaluate motivation in the educational area; for this reason, carrying out validation for Puerto Rico is proposed. The construct validity and internal consistency of the AMS will be evaluated to benefit future researchers interested in the educational area in the Puerto Rican population.

Method

Research Design and Procedures

Following the classifications of Ato et al. (2013), this research was framed within the non-experimental model, under an instrumental model. The Institutional Review Board of Carlos Albizu University in San Juan, Puerto Rico, approved the research project. Data collection was made online (internet), and volunteers were recruited by propagating a paid ad on social media, directing them to informed consent and the survey. The consent included the purpose of the study, the inclusion criteria, the voluntary nature of the study, the possible risks, and benefits, as well as the right to withdraw from the study at any time.

Participants

A total of 300 students at the graduate level participated in the present investigation with ages ranging from 21 to 40 years, with a mean age equal to 29.14 and a standard deviation equal to 4.87. Table 1 shows that most of the students were female (77.3%), 65.0% were studying for a master's degree, 72.3% of the sample was between the first and third year of study, 86.7% reported having an academic average between 3.50 to 4.00, and 53.7% indicated that they studied daily between one to three hours.

Measurement

Academic Motivation Scale, Spanish version (AMS; Núñez et al., 2006). The scale contains seven subscales with four items each for a total of 28 items. Of these subscales, there are three that evaluate intrinsic motivation (IM): IM to knowledge, IM to achievement and IM to stimulating experiences. At the same time, three subscales measure extrinsic motivation (EM): external regulation, introjected regulation, and identified regulation. Finally, there is the subscale that measures amotivation. All the items answer the question, *Why are you going to college?* and the scale is anchored on a seven-point Likert scale from 1 (*Does not correspond at all*) to 7 (*It totally corresponds*), with an intermediate score of 4 (*It moderately corresponds*). The confirmatory factor analysis results using the modeling of structural equations found by Alonso et al. (2006) support the internal structure of seven factors and the correlations between the subscales with academic self-concept support the construct validity of the scale. The reliability of the subscales, according to Núñez et al. (2010), were acceptable since they fluctuated between .68 to .79 using Cronbach's alpha technique.

Data Analysis

The data were analyzed, first, with the IBM-SPSS version 28.0 program, and descriptive statistics, correlation, reliability, and item analysis were performed with it. In addition, we performed several confirmatory factors analyses

Table 1
Sociodemographic data of the study participants. (*n* = 300).

Variable	Frequency	Percent	Variable	Frequency	Percent
Gender			**Academic Year**		
Female	232	77.3	First	80	26.7
Male	67	22.3	Second	85	28.3
Program			Third	52	17.3
Master	195	65.0	Fourth	26	8.7
Doctorate	105	35.0	=>Fifth	57	19.0
GPA			**Hours Dedicated Daily to Studying**		
3.50 - 4.00	260	86.7	1-3	161	53.7
3.00 - 3.49	34	11.3	3-5	91	30.3
2.50 - 2.99	4	1.3	=>5	48	16.0
2.00 - 2.49	2	.7			

and invariance testing by gender and age of the Academic Motivation Scale using the weighted least squares-mean and variance adjusted (WLSMV) estimator with the "lavaan" package of the R3.6.3 program (Rosseel, 2012), which robustly deals with potentially non-normal data with items treated as ordinal (Li, 2016a, 2016b). To evaluate the results of the CFA, several fit indices of the structural equation models were used. Kline (2016) recommends the use of at least four fit indices, although more can be reported. One of the indices that is reported is Chi-Square (χ^2). This is a fundamental index of absolute adjustment and it is basically the same one that is used when the researcher wants to examine the association between nominal variables. However, the crucial difference when used as an index of fit in the structural equations model is that the researcher looks for no differences between the matrices to support that the tested model is representative of the data (Hair et al., 2019). Given that the χ^2 is sensitive to the sample size and therefore the probability of rejecting the hypothesized model increases when the sample size increases, it is recommended to take into account other indices (Marsh et al., 1996). In this way, the Root Mean Square Error of Approximation (RMSEA; Byrne, 2016; Hu & Bentler, 1999) was used, values ranging from .08 to .10 are considered as mediocres, less than .08 for the RMSEA indicate an acceptable fit, while values equal to .05 or less indicate a good fit of the model (Browne & Cudeck, 1989; MacCallum et al., 1996).

In addition, Standardized Square Root Mean Residual (SRMR; Hu & Bentler, 1999) was used, which examines the average difference between predicted and observed variances and covariances, based on the residual standard error. The lower the SRMR, the better the fit of the model; and to consider it an acceptable model it must be or close to .08, but it is preferred to be equal to or less than .05 (Hu & Bentler, 1999). On the other hand, the Bentler Comparative Fit Index (CFI) was used as an increased fit index to compare the theoretical model with the null model, which assumes that the latent variables of the model do not correlate with each other and values greater than .90 are considered acceptable (Hair et al., 2019). Another increased adjustment index is the Tucker-Lewis Index (TLI) that reflects the proportion in which the theoretical model improves the adjustment in relation to the null model (Littlewood-Zimmerman & Bernal-García, 2011; Tucker & Lewis, 1973). Values greater than .90 are considered acceptable.

Four competitive models were tested: a first model sought to examine the seven factors proposed and found by the authors of the scale (Núñez et al., 2010; Núñez et al., 2006); a second model was also evaluated in order to analyze a model of three factors, one for extrinsic motivation, another for intrinsic motivation, and a third intended to measure amotivation; a third model proposed an unifactorial internal structure in which all items loaded in just one factor. As it can be appreciated in Table 3, the best fitted model was the seven-factor model. Finally, a bifactor model was also tested which specifies that a general factor influences all items in addition to the seven specific factors. Furthermore, to examine whether there is a continuum in the general factor as a source of item variability, other indicators were applied to assess the general factor. The hierarchical omega (ω_H) refers to the amount of total variance that can be attributed to the overall factor (Flores-Kanter et al., 2018). The explained common variance (ECV) is also used, which can be interpreted as the amount of common variance of all items that is due to the overall factor. The percentage of uncontaminated correlations (PUC) are employed, which provides information on the percentage of correlations not contaminated by multidimensionality (Rodriguez et al., 2016). Also, the percentage of uncontaminated correlations (ECV) is utilized, which is an indicator of unidimensionality; an ECV greater than .60 would indicate that there is little common variance between the factors other than the overall factor (Rodriguez et al., 2015). At the item level, the ECV-I was implemented, whose interpretation is similar to the ECV, indicating the percentage of the true variance of each item explained by the general factor. This coefficient requires that its magnitudes be greater than .60. Moreover, the average relative parameter bias (ARPB) is used, which is a measure for examining the difference between the factor loading of a unidimensional model and the general factor loading of the bifactor model (Rodriguez et al., 2016). A maximum difference of .12 to .15 may be acceptable. Finally, the factor loadings suggested by the literature (e.g., Reise et al, 2010) were examined by calculating the arithmetic means of the items. Ferrando and Lorenzo-Seva (2017) indicate that factor loading means lower than .30 in any specific factor can be considered as secondary evidence of unidimensionality.

Results

Table 2 shows the descriptive statistics of the 28 items of the AMS (mean, standard deviation, skewness and kurtosis). Item 3 had the highest mean, skewness, and kurtosis among all items, while item 21 had the highest standard deviation.

In terms of the results of the CFAs, the results can be seen in Table 3, in which it can be seen that the seven-factor model obtained the best fit indices, although the SRMR was above the threshold of .05. The bifactor model was the second best regarding fit indices and interestingly did not outperform the seven-factor model.

Table 2
Descriptive statistics of the 28 items of the Academic Motivation Scale (AMS).

# Item	Mean	SD	Skewness	Kurtosis	# Item	Mean	SD	Skewness	Kurtosis
1	4.88	2.27	-0.616	-1.115	15	5.47	1.91	-1.060	-.026
2	6.30	1.16	-1.913	3.543	16	5.67	1.63	-1.157	.520
3	6.50	1.07	-2.804	8.810	17	5.38	1.97	-1.091	-.004
4	4.28	2.05	-.145	-1.208	18	4.43	2.11	-.292	-1.250
5	1.91	1.67	1.952	2.777	19	1.58	1.50	2.748	6.473
6	6.19	1.25	-1.800	3.224	20	5.43	1.91	-1.060	-.019
7	4.96	2.33	-0.673	-1.159	21	4.39	2.36	-.282	-1.490
8	5.73	1.79	-1.458	1.155	22	5.83	1.67	-1.495	1.416
9	5.99	1.50	-1.691	2.387	23	6.13	1.41	-1858	2.954
10	6.25	1.30	-2.224	5.084	24	6.16	1.45	-2.046	3.786
11	4.14	2.05	.004	-1.245	25	4.99	1.94	-.609	-.785
12	2.58	2.13	1.080	-.327	26	1.70	1.64	2.429	4.635
13	6.15	1.40	-1.821	2.982	27	4.67	2.19	-.505	-1.137
14	4.78	2.22	-.544	-1.174	28	5.49	1.95	-1.108	.034

Note. $n = 300$; SD = Standard deviation.

Table 3
Fit indices obtained by the four competitive models of the Academic Motivation Scale.

Fit Index/Model	7-Factor	3-Factor	1-Factor	Bifactor
χ^2 (*df*)	707.007* (329)	2068.530* (347)	5905.536* (350)	1293.384* (322)
SRMR	.079	.126	.222	.108
RMSEA (CI)	.062 (.056 - .068)	.129 (.123 - .134)	.230 (.225 - .236)	.143 (.134 - .152)
CFI	.992	.962	.876	.979
TLI	.990	.958	.866	.975

Note. $n = 300$, $*p < .05$.

Table 4 shows the factor loadings (λ), discrimination indices (R_{bis}), reliability coefficients, and the average variance extracted (AVE) of the subscales of the AMS. All subscales obtained a reliability coefficient greater than .70 using Cronbach's alpha and McDonalds' omega with their respective confidence intervals; moreover, all subscales obtained an average variance extracted greater than .50 as recommended by some literature (Fornell & Larcker, 1981).

Table 4
Factor loadings (λ), discrimination index (r_{bis}), average variance extracted (AVE), and reliability of the items belonging to the AMS by subscale.

Subscale	Item	r_{bis}	λ	$λ^2$	AVE	Reliability	
						(CI)	(CI)
External Regulation	me1	.409	.438	.192	.615	.781 (.715 - .827)	.728 (.728 - .831)
	me8	.709	.863	.746			
	me15	.618	.872	.761			
	me22	.676	.872	.760			
Introjected Regulation	me7	.655	.775	.601	.719	.858 (.827 - .886)	.859 (.829 - .887)
	me14	.709	.841	.708			
	me21	.730	.836	.698			
	me28	.732	.932	.869			
Identified Regulation	me3	.462	.755	.570	.623	.750 (.660 - .810)	.764 (.677 - .824)
	me10	.611	.782	.611			
	me17	.550	.792	.627			
	me24	.650	.824	.679			
MI to Knowledge	me2	.622	.749	.561	.692	.830 (.772 - .869)	.836 (.787 - .878)
	me9	.712	.859	.738			
	me16	.571	.788	.621			
	me23	.763	.920	.846			
MI to Achievement	me6	.594	.812	.660	.690	.798 (.745 - .839)	.805 (.752 - .846)
	me13	.710	.889	.791			

Subscale	Item	r_{bis}	λ	λ^2	AVE	Reliability (CI)	(CI)
	me20	.668	.814	.663			
	me27	.583	.803	.644			
	me4	.490	.675	.456	.700	.848 (.810 - .878)	.859 (.828 - .885)
MI Stimulating Experiences	me11	.754	.827	.685			
	me18	.800	.912	.833			
	me25	.719	.906	.820			
Amotivation	me5	.734	.886	.786	.831	.872 (.821 - .906)	.871 (.821 - .906)
	me12	.688	.850	.723			
	me19	.780	.965	.931			
	me26	.755	.923	.853			

Note. *n* = 300; ∝ = Cronbach's Alpha; ω = McDonald's Omega; CI = Confidence Interval.

Despite the fact that the bifactor model did not obtain the best fit indices, we believe it is necessary to present the results of this model, including the ancillary statistics that can help determine the unidimensionality or multidimensionality of the AMS (see Table 5). It is important to point out that 20 of the 28 items of the AMS obtained stronger factor loadings on the general factor in contrast to 8 items that obtained stronger factor loadings on its respective specific factor. For example, the factor loading mean of the general factor was λ_{Mean} = .549 and the factor loading mean of the specific factors fluctuated between λ_{Mean} = .154 and λ_{Mean} = .879, being the lowest of the IMA subscale and the highest the amotivation subscale. Therefore, the average factor loadings of the subscales were λ_{Mean} = .485. Regarding the ω_H of the general factor, it obtained a value of .857, providing information on the amount of total variance that can be attributed to the general factor (Zinbarg et al., 2006), which is well beyond the threshold of .80 and probably it might be possible to consider the AMS as a unidimensional measure. Moreover, ω_{HS} values obtained by the subscales fluctuated between ω_{HS} =.032 and ω_{HS} = .897 in which IMA subscale obtained the lowest value and the amotivation subscale the highest. There are authors (e.g., Smits et al., 2015), that consider values of ω_{HS} between .20 and .30 is acceptable because they reflect a moderate proportion of the variance; however, there are other authors (e.g., Arias et al., 2018) who consider values less than .50 as an impediment to interpreting it as a factor. On the other hand, although the PUC was high (.889), the magnitude of the ECV (.580) was less than .70, which suggests that the data is not unidimensional enough (Quinn, 2014; Reise et al., 2013; Rodriguez et al., 2016). In terms of the ECV-I, 8 items have a significant influence on the overall factor: me3 and me17 (IndR), me16 and me23 (IMK), me13, me20 and me27 (IMA), and me12 (Amot). In other words, these are items that are essentially explained by the general factor and are better indicators of the general factor than of its specific factor as suggested by some literature (e.g., Montes & Sánchez, 2019). On the other hand, there are some items that seem to be good indicators for both the general factor and its respective specific factor, with corresponding ECV-I values around .50, such as items me15 and me22 of the ER subscale, and items me7 and me21 of the IntR subscale. Meanwhile, the

Table 5
Bifactor-CFA factor loadings of unifactor (Unif), general (GF), specific factors and ancillary statistics results.

Scale	Item	Unif	GF	Specific Factors							ECV-I	ARPB
				ER	IntR	IndR	IMK	IMA	IMSE	Amot		
ER	me1	.275	.244	.492							.197	.127
	me8	.659	.593	.675							.436	.111
	me15	.669	.625	.547							.566	.070
	me22	.674	.614	.608							.505	.098
IntR	me7	.652	.604		.522						.572	.079
	me14	.723	.674		.504						.641	.073
	me21	.711	.649		.572						.563	.096
	me28	.798	.766		.467						.729	.042
IndR	me3	.661	.675			.238					**.889**	.021
	me10	.690	.689			.445					.706	.001
	me17	.687	.712			.311					**.840**	.035
	me24	.725	.731			.416					.755	.008
IMK	me2	.676	.653				.484				.645	.035
	me9	.780	.775				.416				.776	.006
	me16	.713	.730				.206				**.926**	.023
	me23	.836	.830				.360				**.842**	.007
IMA	me6	.763	.783					.591			.637	.026
	me13	.836	.860					.178			**.959**	.028
	me20	.757	.806					.008			1.00	.061
	me27	.736	.804					-.163			**.961**	.085
IMSE	me4	.515	.533						.273		.792	.034
	me11	.701	.528						.690		.369	.328
	me18	.794	.625						.730		.423	.270
	me25	.770	.710						.480		.686	.085
Amot	me5	-.590	-.331							.809	.143	-.782
	me12	-.493	-.246							.811	**.840**	1.004
	me19	-.761	-.165							.955	.029	-3.612
	me26	-.702	-.112							.937	.014	-5.268
λ_{Mean}			.549	.581	.516	.353	.367	.154	.543	.878		
PUC			.889									
ECV			.580									
ARPB			-.318									
ω_H			.857									
ω_{HS}				.483	.338	.175	.175	.032	.404	.897		

ARPB value was equal to .318, which exceeds the threshold of .12 to .15 (Rodriguez et al., 2016), which is considered an acceptable criterion and therefore the ARPB value presents an inconsistency between the factor loadings of the unidimensional model and the general factor of the bifactor model. However, when we look at the ARPB of each item, we can see that only six items exceeded the ARPB criteria: me11 and me18 (IMSE) and the four items of the amotivation subscale (me5, me12, me19 and me26).

Since the seven-factor model was the best fitted, we examined the measurement invariance of the AMS by gender and age. Thus, measurement invariance was done with a bottom-up approach, from an unrestricted model to a model with strong restriction (Stark et al., 2006). Thus, we tested an unrestricted model of equality (configurational invariance) and continued with successive restrictions applied to factor loadings and thresholds (metric invariance), and intercepts (scalar invariance). Considering the sample size (> 300; Chen, 2007), the invariance criteria were: CFI < .010, SRMR < .030 and RMSEA < .015 (Chen, 2007). As such, measurement invariance in every group analyzed (i.e., gender and age) were good and complied with the established criteria. The differences between fit indices (Δ_{SRMR}, Δ_{RMSEA}, Δ_{CFI}, and Δ_{TLI}) were within limit, suggesting that the AMS was invariant among those groups (see Table 6).

Finally, the scores between the subscales of the AMS were correlated to demonstrate the presence of a continuum that goes from amotivation to IM. We should find high and positive correlations between the adjacent subscales and negative correlations among the scales opposite the construct on the continuum (Deci & Ryan, 1985). In Table 7, the correlations of the covariances (under the diagonal) that were high and strong between the latent variable IM-knowledge and IM-achievement, but IM-achievement with introjected regulation and identified regulation stand out. Also noteworthy are the correlations of the covariances between the latent variable of amotivation and the remaining latent variables close to zero and other negative ones. Similarly, correlations of the observed scores (above the diagonal) can be appreciated between IM at achievement and robust correlation introjected regulation.

Discussion

This study aimed to examine the internal structure and psychometric properties of the

Table 6

Measurement invariance of the Academic Motivation Scale by gender and age.

Model	χ^2 (*df*)	SRMR	RMSEA	CFI	TLI	Model of Reference	$\Delta\chi^2$	ΔSRMR	ΔRMSEA	ΔCFI	ΔTLI
Multigroup analysis by gender (male/female)											
1: Configural	916.06* (658)	.086	.051	.995	.994	-----	-----	-----	-----	-----	-----
2: Metric	1,027.03* (679)	.090	.059	.993	.992	1	+110.97	+.004	+.008	-.002	-.002
3: Scalar	993.54* (806)	.086	.040	.996	.996	2	-33.49	-.004	-.019	+.003	+.004
Multigroup analysis by age (21-30 /31-40)											
1: Configural	1,066.35* (658)	.091	.065	.992	.991	-----	-----	-----	-----	-----	-----
2: Metric	1,121.11* (679)	.092	.066	.991	.990	1	+54.76	+.001	+.001	-.001	-.001
3: Scalar	1,140.07* (806)	.091	.053	.993	.994	2	+18.96	-.001	-.013	+.002	+.004

Note. *p < .05; *df* = degree of freedom.

Table 7
Correlation matrix between latent variables (under the diagonal) and observed variables (above the diagonal) of subscales of the Academic Motivation Scale.

Subscale	1	2	3	4	5	6	7
1. External Regulation	1	.524**	.587**	.272**	.389**	.276**	.055
2. Introjected Regulation	.717**	1	.495**	.429**	.682**	.423**	.081
3. Identified Regulation	.791**	.682**	1	.569**	.583**	.416**	-.251**
4. IM-Knowledge	.465**	.597**	.819**	1	.717**	.636**	-.249**
5. IM-Achievement	.587**	.846**	.791**	.884**	1	.615**	-.176**
6. IM-Stimulating Experiences	.376**	.519**	.560**	.797**	.732**	1	-.025
7. Amotivation	.032	.067	-.427**	-.366**	-.318**	-.028	1

Note. $n = 300$; $*p < .05$; $**p < .01$.

AMS in a sample of graduate students in Puerto Rico. The results of the confirmatory factor analysis supported the internal structure of seven factors of the AMS, given that it was the model that obtained the best-fit indices and which is consistent with the theory used by the authors to construct it. Moreover, as reported in other studies (e.g., Alonso et al., 2006), these fit indices were achieved without correlating errors between the indicators. This is probably because a polychoric matrix and a more appropriate estimator (WLSMV) were used to perform the data analyses instead of the maximum likelihood estimator. On the contrary, even though the seven-factor model surpassed the bifactor model, some ancillary statistics suggest that the AMS could be more unidimensional than multidimensional due to the high value obtained from PUC. However, since the ECV is less than .70, this could also suggest multidimensionality, as proposed by the authors of the test (Núñez et al., 2010). These results of the ancillary statistics could probably suggest that both the seven factors and a general factor provide relevant information for the understanding of the data obtained from the AMS. It should be noted that the items of the amotivation subscale were the only ones with negative factor loadings both in the unidimensional model and in the general factor of the bifactor model, which could be affecting the values of the supplementary statistics of the bifactor model and making the unidimensionality/multidimensionality interpretation of the AMS more difficult.

The present study provides insight into measurement invariances of the AMS across gender and age. Since the seven-factor model obtained the best-fit indices and is consonant with the theory in which the AMS was developed, we tested the measurement invariance of this model. We tested the measurement invariances of AMS among students at different universities in Puerto Rico. Exploration on the first two levels revealed metric or factor loading invariance (i.e., weak measurement invariance) and scalar invariance (i.e., strong measurement invariance) of the seven-factor model across gender and age. Metric invariance is important to ensure the measure across multiple groups is on the same scale or that all groups' factors are measured similarly (Meredith & Teresi, 2006; Vandenberg & Lance, 2000; Wang & Wang, 2012). Scalar invariance refers to the item intercept being invariant across multiple groups in the present study. This indicates that none of the groups tends to respond systematically higher or lower to the items of scales than other groups (Meredith & Teresi, 2006; Vandenberg &

Lance, 2000; Wang & Wang, 2012). The present study met both invariance requirements. These results confirm that the compared groups had an equivalent understanding of each of the 28 items in the measure, an important prerequisite for making a meaningful comparison between groups on academic motivation. Researchers have argued that error variance invariance (i.e., strict measurement invariance) is not required for substantive analyses in many disciplines, and such invariance is considered unnecessary (Wang & Wang, 2012).

In terms of the correlations between the subscales of the AMS, it was possible to appreciate that, in general, it supports the conceptual framework of Deci and Ryan (1985) regarding the presence of a continuum that goes from amotivation to IM, where adjacent scales show higher correlations than opposite ones on the continuum. However, the IM to Achievement subscale presented higher covariance correlations with Introjected Regulation and Identified Regulation than with its adjacent dimensions of IM to Knowledge and MI to Stimulating Experiences, these results being similar to other studies (Cokley et al., 2001; Fairchild et al., 2005; Nuñez et al., 2010; Nuñez et al., 2006; Vallerand et al., 1993). Thus, we agree with Cokley et al. (2000) and Nuñez et al. (2006), who indicate that this could be because the difference between the EM and IM constructs is not as categorical as the self-determination theory proposes. Therefore, we echo Nuñez et al. (2006) that the items of the Introjected Regulation, Identified Regulation, and MI Achievement subscales should be reviewed for future research since they could be sharing a common factor given that these dimensions have some satisfaction, prove that they can achieve proposed goals and achieve a better future.

Limitations and Recommendations

The results, while satisfactory, should be interpreted with caution due to certain limitations of the study. Although the findings are consistent with the proposal by Deci and Ryan (1985) and exceed those of the bifactor model, the high correlations between the MI and EM subscales could be indicative that they do not differ as much as the theory supposes or that they come from a common factor as suggested by some of the ancillary statistics (e.g., PUC) of the bifactor model.

The bifactor model also presents some drawbacks that must be considered. As previously stated, good statistical results do not guarantee the existence of a general factor (Bonifay et al., 2017). Nonetheless, a CFA only allows the items of each factor to load on them, but it does not allow the items to load on other factors, which tends to be unrealistic with the psychological constructs, (Furr, 2022) since they tend to relate. In this way, for future research, it is recommended that the sample of students is expanded and that exploratory structural equation modeling (ESEM) and bifactor ESEM should be carried out to be clear about the unidimensionality/multidimensionality of the AMS and that the application ESEM and bifactor ESEM might help in this endeavor.

Conclusion

Results of the current study provide evidence that supports the internal structure of the AMS and the ancillary statistics use; additionally the bifactor model presents some interesting information about the possible unidimensional or multidimensional uses of the AMS. The subscales of the AMS obtained good reliability coefficients, and the AMS appears to be invariant among gender and age, which permits comparison among these groups. Therefore, the AMS is useful in the educational context with graduate students in Puerto Rico.

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