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The Role of Learning Strategies and Motivation in Academic Performance: A Study of University Students

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Abstract: *This study explores the relationship between motivational and learning strategies and academic performance among university students in Romania, an area that remains underexplored, particularly in relation to academic performance across different study programs. Data were collected from students enrolled in full-time and hybrid study programs in the field of educational science (N = 225). The results reveal statistically significant findings from the subscale analysis, with a model precision of 58.7%. While the holistic Motivation Scale and Learning Strategy Scale did not significantly impact academic performance, specific subscales emerged as influential predictors. Key motivational strategies, such as task value, control of learning beliefs, self-efficacy, and learning strategies like effort regulation, metacognitive self-regulation, and help-seeking, were found to impact academic performance significantly. Additionally, the frequency of study programs (full-time vs. hybrid) emerged as a significant moderator, particularly for lower-performing students. These findings highlight the importance of fostering students' beliefs in their learning abilities, their perceived control over learning outcomes, and their valuation of academic tasks. The study underscores the need for targeted interventions to enhance students' motivation and self-regulation, ultimately improving academic performance. These insights offer valuable guidance for educators and policymakers aiming to design effective support systems for students in higher education.*

Keywords: *academic performance; higher education; student motivation; learning strategies; self-regulation.*

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Introduction

Education embodies a complex ecosystem where various psychological and behavioral factors interact to shape students' academic paths. Extensive research has demonstrated that motivation and learning strategies are key determinants of educational success (Pintrich & De Groot, 1990; Zimmerman, 2000). Efficient learning implies the student's ability to combine strategies, correlate them with objectives, and increase the motivation for achievement (Frumos et al., 2024). Furthermore, efficient learning emphasizes the practical component of skills (learning to do) or learning abilities (learn to learn) within the context of lifelong learning.

Despite the wealth of studies on these constructs, specific academic contexts, particularly in Eastern Europe, remain underexplored. Romania's dynamic higher education landscape, characterized by ongoing reforms and internationalization (Hatos, 2016), provides a compelling setting for examining the intricate relationships among student motivation, learning approaches, and academic success (Mourad et al., 2021; Paisey & Paisey, 2004; Syih, 2023). By examining the underlying mechanisms that contribute to student success. this study offers valuable insights into Romanian educational dynamics and the broader motivational and learning processes influencing the academic results of college students.

The influence of specific motivational strategies

Academic motivation refers to students' intrinsic desire to learn within an educational context, significantly influencing both their learning strategies and the effort they exert (Stroud & Reynolds, 2006). The research focuses on specific motivational subcomponents that have been proven to predict academic performance:

- Intrinsic Goal Orientation: This emphasizes learning and mastery of information and is expected to positively affect students' academic performance (Dokhykh, 2021).
- Extrinsic Goal Orientation emphasizes grades and external approval. Research indicates that extrinsic motivation also positively influences academic performance (Khaliq, 2023; Dokhykh, 2021).
- Task Value: This refers to students' perception of the importance, utility, and engaging nature of the course content (Duncan & Mckeachie, 1991; Duncan & McKeachie, 2005). High task value can reduce academic procrastination (Lee, 2024), and serves as a strong predictor of academic performance, for students with low self-esteem significant anxiety and test anxiety(Özgüngör & Paksu, 2017).

• Control of Learning Beliefs: These are students' perceptions that their academic performance is conditioned by their effort. Such adaptive cognitions are associated with high academic performance (Floden & Reiter, 2024).

• Self-efficacy for Learning and Performance: This refers to students' expectations regarding their capacity to complete an educational task. High self-efficacy is correlated with establishing challenging objectives, employing effective learning strategies, and persisting through complex tasks (Musa, 2020), potentially leading to high academic performance (Azila-Gbettor et al., 2022; Clipa et al., 2022).

• Test anxiety refers to students' concerns regarding examination achievement and their anticipated evaluation, representing a prevalent issue among university students. In this context, test anxiety is characterized by cognitive and emotional components that can negatively impact academic performance (Florescu et al., 2023; Indrieș & Bochiș, 2019; Safeer & Shah, 2019; Trifoni & Shahini, 2011).

Based on the literature that supports the positive impact of these key motivational components on academic outcomes, *Hypothesis 1* is formulated*: Students with higher levels of motivational strategies would demonstrate better academic performance.*

The impact of specific learning strategies

The ultimate aim of identifying and developing learning strategies is to increase the effectiveness of learning and, implicitly, academic performance. Academic success depends on *how* students learn; therefore, we will review the most well-known strategies:

• Rehearsal: Refers to the repetition of words to facilitate information recall. Existing studies demonstrate that repetition increases the duration of information retention in memory (Sotardi & Brogt, 2020). Therefore, we expect rehearsal to have a positive impact on students' academic performance.

• Elaboration encompasses the capacity for summarizing and paraphrasing content. Sotardi & Brogt (2020) found that elaboration strategies strongly influenced academic self-efficacy, while rehearsal strategies increased student anxiety. We observe, therefore, that the efficacy of these elaboration strategies can vary depending on multiple criteria, including academic performance level, with average- and high-performing students benefiting more than low-performing students (Wood & Olivier, 2007).

• Organization refers to the manner and type of cognitive organizers utilized as a learning strategy: schemas, graphics, sketches, tables, etc. Regarding the efficacy of this strategy, Kansizoglu (2017) meta-analysis

study results indicate significant positive effects on academic performance in higher education, with the authors emphasizing that graphic organizers' effectiveness appears consistent across organizer types, learning domains, and respondents' study levels.

- Critical thinking as a learning strategy refers to critically evaluating ideas and recontextualizing information, and it positively correlates with reflective and creative thinking, thereby contributing to students' academic success (Akpur, 2020).
- Metacognitive Self-Regulation: Involves planning, monitoring personal understanding, and adjusting strategies. It positively influences performance by enabling students to reflect on the effectiveness of their learning strategies (Blackmore et al., 2021).
- Help-Seeking: This strategy (from peers and/or teachers) is positively associated with academic success, especially for students who learn more online and are less confident Broadbent & Howe (2023).
- Other Strategies: Strategies like Time and Study Environment Management (Razali et al., 2018), Effort Regulation (Han et al., 2023), and Peer Learning (Granger-Serrano & Villarraga-Orjuela, 2021; Guyaho, 2020) are also supported in the literature as relevant for academic success.

Given that the effectiveness of individual strategies (such as effort regulation, metacognitive self-regulation, and help-seeking) has been demonstrated as very important for academic success, *Hypothesis 2* posits *that students with more effective learning strategies would achieve higher academic performance.*

The moderating role of the study program

While the roles of motivation and strategies are well-established, studies comparing their effectiveness based on the study program (full-time/hybrid) are largely lacking.

Study programs classified as *hybrid* or *part-time* possess distinct characteristics compared to *full-time* programs, such as replacing teaching hours with individual study activities and delivering resources via distance education media. Furthermore, contextual factors like part-time employment, financial hardship, and family responsibilities contribute to lower attendance, while higher attendance generally leads to better grades and academic performance (Syih, 2023).

Considering the structural and contextual differences between these programs, it is essential to investigate whether the study environment influences how motivational and learning strategies operate. Therefore, *Hypothesis 3 aims to examine the moderating role of the study program (full-time vs. hybrid) on the relationship between motivational and learning strategies and academic performance.*

Methods

Study aims and hypotheses

This study investigated the relationship between motivational and learning strategies and academic performance among Romanian university students enrolled in educational science programs. Specifically, the study aimed to examine:

1. The influence of motivational strategies (intrinsic goal orientation, task value, control of learning beliefs, and self-efficacy) on academic performance. Students with higher levels of these motivational strategies would demonstrate better academic performance.
2. The impact of learning strategies (rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment management, effort regulation, peer learning, and help-seeking) on academic performance. Students with more effective learning strategies would achieve higher academic performance.
3. The moderating role of the study program (full-time vs. hybrid) on the relationship between motivational and learning strategies and academic performance. The effectiveness of specific motivational and learning strategies may vary depending on the study program.

Instruments

The questionnaire, administered online via Google Forms, was adapted from Duncan & McKeachie's *Motivated Strategies for Learning Questionnaire* (MSLQ) (Duncan & McKeachie, 2005). After obtaining author permission, the 81 MSLQ items were translated into Romanian. In addition to the MSLQ items, socio-demographic variables were collected, including university affiliation (University of Oradea and "Stefan cel Mare" University of Suceava), specialization, form of attendance (full-time study program /hybrid study program), and year of study. First-year students provided their Baccalaureate exam average, while students in other years reported their average grades from the previous academic year. All responses were self-reported.

Sample and data

Data were collected between 21 October 2023 and 21 January 2024 from students in the Faculty of Socio-Human Sciences at the University of Oradea and "Stefan cel Mare" University of Suceava. After excluding participants who did not consent to data processing according to the GDPR agreement, the final sample size was N = 225. Further details on the sample composition are presented in Table 1.

Table 1. Variables Characteristics

Subscales	Variables	Measurement	Description
Independent Variable	Frequency programme	Dummy (1=full-time study program)	Hybrid study program=30.2% Full-time study program frequency=69.8%
Independent Variables (Motivation SCALE)	Intrinsic goal orientation	Scale	min=2.75; max=5.00; mean=4.18; s.d.=.55;
	Extrinsic goal orientation	Scale	min=1.00; max=5.00; mean=3.59; s.d.=.79;
	Task value	Scale	min=2.67; max=5.00; mean=4.33; s.d.=.57;
	Control of learning beliefs	Scale	min=2.25; max=5.00; mean=4.27; s.d.=.58;
	Self-efficacy for learning and achievement	Scale	min=2.13; max=5.00; mean=3.95; s.d.=.63;
	Test anxiety	Scale	min=1.00; max=5.00; mean=3.16; s.d.=1.02;
Independent Variables (Learning strategies)	Rehearsal	Scale	min=1.25; max=5.00; mean=3.64; s.d.=.75;
	Elaboration	Scale	min=2.17; max=5.00; mean=3.89; s.d.=.69;
	Organization	Scale	min=1.50; max=5.00; mean=3.99; s.d.=.76;
	Critical thinking	Scale	min=1.00; max=5.00; mean=3.16; s.d.=.77;
	Metacognitive self-regulation	Scale	min=1.75; max=5.00; mean=3.71; s.d.=.53;
	Managing time and study environment	Scale	min=1.75; max=5.00; mean=3.70; s.d.=.66;
	Effort regulation	Scale	min=1.00; max=5.00; mean=3.52; s.d.=.63;
	Peer learning	Scale	min=1.00; max=5.00; mean=3.17; s.d.=.94;
	Help-Seeking	Scale	min=1.00; max=5.00; mean=3.15; s.d.=.77;
Dependent Variable	Academic performance	Numeric - Categorical	1= under 6.99 (3.6%); 2=7.00-7.99 (13.3%); 3=8.00-8.99 (38.2%); 4=9.00-10.00 (44.9%);

As mentioned in the instrument presentation, we used two scales: *motivation* and *learning strategies*, each with its subscales. Therefore, we calculated the Cronbach's alpha coefficient to identify the internal reliability. Cronbach's alpha for *the Motivation Scale* =.631, which means our scale consistency is questionable. If the item related to *Test Anxiety* was deleted, the Cronbach's alpha score increased to .796, and if the item related to *Extrinsic Goal Orientation* was deleted, the score increased to **.825.** We recalculated the average score of the remaining items from the motivation scale, and the regression results can be seen below. The Cronbach's alpha for the *Learning Strategies Scale* = **.845** – score indicating a very good internal consistency of the scale.

Results

Multinomial logistic regression was chosen as the data analysis method due to the ordinal categorical nature of the dependent variable, *Academic Performance*. This method allows for examining the relationship between multiple independent variables and the probability of belonging to a specific category of the dependent variable. Before conducting the regression, the data were screened to ensure that the assumptions of multinomial logistic regression were met. Multicollinearity was assessed using Variance Inflation Factors (VIFs). All variables within the motivation and learning strategies scales had VIF values below the recommended threshold of 3, except for *Task Value*, which had a VIF of 3.173. Although slightly above the threshold, this value was deemed acceptable as it only marginally exceeded the limit and did not indicate severe multicollinearity that would significantly impact the stability of the regression coefficients.

a) This section presents the results of *the first logistic regression analysis* examining the relationship between academic performance (categorized into four groups: below 6.99, 7.00–7.99, 8.00–8.99, and 9.00–10.00), learning strategies, motivation, and program frequency (full-time study program vs. hybrid). Table 2 shows the model fitting information. The final model is statistically significant ($\chi^2(9) = 19.989$, $p = .018$), indicating that the included predictors, as a set, improve the model fit compared to the intercept-only model.

Table 2. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	501.500			
Final	481.511	19.989	9	**.018**

Table 3 presents the pseudo R-squared values. Nagelkerke's R^2 is .095, suggesting that the model explains approximately 9.5% of the variance in academic performance. The Cox and Snell and McFadden R^2 values are also provided.

Table 3. Pseudo R-Square

Pseudo R-Square	
Cox and Snell	.085
Nagelkerke	**.095**
McFadden	.040

Table 4 displays the classification matrix for the multinomial logistic regression model.

Table 4. Classification Matrix for Multinomial Logistic Regression Model

Observed	Predicted				
	under 6,99	7,00 - 7,99	8,00 - 8,99	9,00 - 10,00	Percent Correct
Lower than 6,99	0	0	5	3	0.0%
7,00 - 7,99	0	0	13	17	0.0%
8,00 - 8,99	0	0	27	59	31.4%
9,00 - 10,00	0	0	23	78	77.2%
Overall Percentage	0.0%	0.0%	30.2%	69.8%	**46.7%**

The model performs best in predicting the highest academic result category (9.00–10.00), with a 77.2% accuracy rate, suggesting that the predictors (motivational and learning strategies) are particularly effective in identifying high-achieving students. For the 8.00–8.99 category, the model achieved a 31.4% accuracy rate, correctly predicting 27 out of 86 cases; for the 7.00–7.99 and under 6.99 categories, the model failed to make any correct predictions (0.0% accuracy). This suggests that the model struggles to distinguish these lower-performing groups effectively.

The table bellow presents the parameter estimates from the multinomial logistic regression model, illustrating the relationship between each predictor variable and the odds of belonging to a specific academic performance category relative to the reference category (9.00–10.00). The predictors include the Learning Strategy Scale, Motivation Scale, and Study Program Frequency (full-time vs. hybrid). The academic performance categories are below 6.99, 7.00–7.99, 8.00–8.99, and 9.00–10.00 (reference category).

Table 5. Parameter estimates for Multinomial Logistic Regression Model predicting academic performance

Academic performance[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
lower than 6,99	Intercept	-8.035	4.195	3.668	1	.055			
	Learning_strategy_Scale	-.605	1.028	.347	1	.556	.546	.073	4.092
	Motivation_Scale	1.609	1.142	1.986	1	.159	4.999	.533	46.866
	[Full study program=0]	2.540	.866	8.606	1	**.003**	**12.678**	2.323	69.187
	[Full study program=1]	0[b]	.	.	0	.	.	.	.
7,00 - 7,99	Intercept	2.321	2.106	1.214	1	.271			
	Learning_strategy_Scale	-.931	.544	2.925	1	.087	.394	.136	1.146
	Motivation_Scale	-.148	.607	.059	1	.807	.862	.262	2.836
	[Full study program=0]	.928	.458	4.101	1	**.043**	**2.530**	1.030	6.213
	[Full study program=1]	0[b]	.	.	0	.	.	.	.
8,00 - 8,99	Intercept	1.179	1.472	.641	1	.423			
	Learning_strategy_Scale	-.202	.373	.292	1	.589	.817	.393	1.699
	Motivation_Scale	-.196	.437	.201	1	.654	.822	.349	1.936
	[Full study program=0]	.538	.338	2.528	1	.112	1.713	.882	3.325
	[Full study program=1]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 9,00 - 10,00.

b. This parameter is set to zero because it is redundant.

As shown in Table 5, when analyzed holistically, the Learning Strategy Scale and Motivation Scale did not show statistically significant effects on academic performance across any category ($p > 0.05$). Furthermore, the overall predictive accuracy of this initial model was only 46.7%. This lack of significance, coupled with the questionable internal consistency found for the Motivation Scale (C. alpha = .631), suggests that the aggregate measure was insufficient to capture nuanced effects.

Therefore, given the need for additional insights into the predictors of academic performance, we proceeded with a second multinomial logistic regression analysis utilizing the individual subscales of the MSLQ, as presented in the following section.

This second analysis aimed to determine if the subcomponents of these scales provide additional insights into the predictors of academic performance. Table 6 displays the model fit information for the multinomial logistic regression analysis using the initial scales. The chi-square test comparing the

final model to the null model (intercept only) is statistically significant ($\chi^2(48) = 124.285$, $p < .001$). This indicates that the inclusion of the predictor variables significantly improves the model fit, suggesting that these variables, as a whole, are meaningfully related to academic performance.

Table 6. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	501.500			
Final	377.215	124.285	48	**.000**

Table 7 shows the pseudo R-squared values. Nagelkerke's R^2 is .476, suggesting that the model explains approximately 47.6% of the variance in academic performance. The Cox, Snell, and McFadden R^2 are also presented.

Table 7. Pseudo R-Square

Pseudo R-Square	
Cox and Snell	.424
Nagelkerke	**.476**
McFadden	.248

Table 8 displays the classification matrix, which evaluates the model's predictive accuracy across the academic performance categories. The model's overall prediction accuracy is 58.7%, which suggests that it has moderate predictive power.

Table 8. Classification

Observed	Predicted				
	below 6,99	7,00 - 7,99	8,00 - 8,99	9,00 - 10,00	Percent Correct
below 6,99	8	0	0	0	100.0%
7,00 - 7,99	0	6	14	10	20.0%
8,00 - 8,99	0	3	44	39	51.2%
9,00 - 10,00	0	5	22	74	73.3%
Overall Percentage	3.6%	6.2%	35.6%	54.7%	**58.7%**

The model performs very well in predicting the lowest academic category (below 6.99) and relatively well for the highest category (9.00–10.00), with 100% and 78.2% accuracy, respectively. This suggests that the predictors are particularly effective in identifying students at the extremes of academic performance. Regarding the comparisons of the estimated parameters, for reasons of economy of space, the table with the 9.00 - 10.00 averages of academic performance as the reference category is presented in the appendix to this article, and only the comparisons between categories are

reported. Therefore, we will report our observations according to the variables for which a statistically significant difference was observed. Thus, below, we present the comparisons for *task value, control of learning beliefs, self-efficacy for learning and achievement, and effort regulation.*

- ***Control of learning beliefs (motivational strategy)***

Students who perceive more significant control over their learning and academic achievement

- are 65% less likely to achieve an average of academic results between 7.00 and 7.99 and no higher than 9.00: Exp (b) = 0.34, Sig. < 0.05 (Appendix), therefore at the inverse comparison, they have 2.9 times greater odds of obtaining an academic achievement average above 9.00 rather than between 7.00 - 7.99;
- have 34% higher odds of obtaining an academic achievement average between 7.00 - 7.99 rather than below 6.99: Exp (b) = 1.34, Sig. < 0.05;
- have 2.51 times greater odds of obtaining an academic achievement average between 8.00-8.99 (Exp (b) = 2.51, Sig. < 0.05) rather than below 6.99,

in comparison to students who perceive less control over these aspects.

- ***Self-efficacy for learning and achievement (motivational strategy)***

Students who perceive themselves to be more self-efficient with regard to learning and achievement

- are 81% less likely to achieve an average of academic results between 7.00 and 7.99 and no higher than 9.00 (Exp (b) = 0.186, Sig. < 0.05 - Appendix); thus, in the inverse comparison, they have 5.37 times greater odds of obtaining an academic achievement average above 9.00 than between 7.00 - 7.99 (Exp (b) = 5.371, Sig. < 0.05);
- they have 3.84 times greater odds of obtaining an academic achievement average above 9.00 than between 8.00 - 8.99: Exp (b) = 3.848, Sig. < 0.05; consequently, they have 74% lower odds of obtaining academic achievement averages between 8.00-8.99 rather than higher: Exp (b) = 0.260, Sig. < 0.05;

compared to students who perceive themselves to be less self-efficient with regard to learning and achievement

- ***Task value (motivational strategy)***

Students who place higher value on academic tasks

- have 3.01 times greater odds of obtaining an academic achievement average between 8.00 - 8.99 and not between 9.00 – 10.00: Exp (b) = 3.015, Sig. < 0.05, and for the inverse comparison, they have 66.8% lower odds of obtaining an academic achievement average between 9.00 - 10.00 rather than between 8.00 - 8.99 (Exp (b) = 0.332, Sig. < 0.05).
- have 3.37 times greater odds of obtaining an academic achievement average between 7.00 - 7.99 (Exp (b) = 3.37, Sig. < 0.05) rather than below 6.99, interestingly, in the inverse comparison of categories, the coefficient is not statistically significant;
- have 5.37 times greater odds of obtaining an academic achievement average between 8.00 - 8.99 (Exp (b) = 5.372, Sig. < 0.05) rather than below 6.99; in the inverse comparison of categories, the coefficient is not statistically significant;

compared to students who disregard (value less) educational tasks.

- ***Metacognitive Self-Regulation (learning strategy)***

Students who demonstrate a higher level of metacognitive self-regulation

- have 2.47 times greater odds of obtaining an academic achievement average between 7.00 - 7.99 (Exp (B) = 2.439, Sig. < 0.05) rather than below 6.99;
- have 8.62 times greater odds of obtaining an academic achievement average between 8.00 - 8.99 (Exp (B) = 8.627, Sig. < 0.05) rather than below 6.99;

in comparison to students with lower levels of metacognitive self-regulation

- ***Effort regulation (learning strategy)***

Students who demonstrate a higher level of effort in regulation

- are 81% less likely to achieve an average of academic results between 7.00 and 7.99 and no higher than 9.00 (Exp (b) = 0.431, Sig. < 0.05), or we can say that they have 2.32 times greater odds of obtaining academic achievement averages higher than 9 rather than lower (8.00 – 8.99): Exp (b) = 2.323, Sig. < 0.05.

in comparison to students who perceive themselves as less regulated in regard to effort

- ***Help seeking (learning strategy)***

Students who seek help more frequently

- have 4.66 times greater odds of obtaining an academic achievement average between 7.00-7.99 (rather than lower): Exp (B) = 4.662, Sig. < 0.05; and 4.45 times greater odds of achieving an average between 8.00-8.99 (Exp (B) = 4.455, Sig. < 0.05) than an average academic result below 6.99
- in comparison to students who do not seek help or are more individualistic.

- ***The Study Program***

In the first regression model, when examining both scales together, holistically, the only statistically significant finding is the frequency program, indicating partial support for Hypothesis 3. It seems that students in the hybrid study program are generally 12.6 times greater odds to have academic performance below 6.99 than between 9.00 and 10.00 (Sig. < 0.05) and 2.5 times greater odds to get academic performance between 7.00 - 7.99 instead of 9.00 - 10.00, compared to students in the full-time study program. Instead, the study program does not influence academic results if we compare students with grades between 8.00 - 8.99 and 9.00 - 10.00, with Exp (B) = 1.713, p > 0.05, students in the hybrid program having equal chances with full-time students to obtain academic averages between 8.00 - 8.99 and 9.00 - 10.00.

If the reference category is changed to 8.00 – 8.99 (for reasons of economy of space, only the results will be reported here), the only significant variable remains the frequency program for the comparison between *below 6.99* and *8.00 – 8.99*: Exp (b) = 7.40, Sig. <0.05. This indicates that students enrolled in the hybrid study program are 7.4 times greater odds to have averages below 6.99 instead of 8.00 - 8.99 compared to the full-time study program.

In a surprising way, *in the second regression model*, examining the results on subscales, the study program does not have a significant effect when comparing students with academic averages between 7.00-7.99 vs. 9-10.00, and 8.00-8.99 vs. 9.00-10.00, respectively. Therefore, students from both study programs have similar chances of obtaining averages higher than 7. However, when comparing averages below 6.99 vs. 9.00-10.00, students enrolled in the hybrid program have significantly higher chances of obtaining grades below 6.99 compared to full-time students (see Table 9 in Annex).

Discussion and conclusions

This study investigated the relationship between motivational and learning strategies and academic achievement among university students. The results are statistically significant, with a model precision of 58.7%. The findings highlight the importance of fostering students' belief in their ability to learn and exert control over their learning, as well as their perception of the relevance and value of the academic tasks they are asked to perform.

Contrary to expectations, the holistic *Motivation Scale* did not show statistically significant effects on academic performance ($p > 0.05$) in the multinomial logistic regression model. This initial failure can be explicitly linked to the questionable consistency of the aggregate Motivation Scale, evidenced by a low Cronbach's alpha coefficient of .631. This low reliability indicates that the composite score did not function as a cohesive measure, potentially masking the strong predictive contributions of specific sub-components. For instance, removing Test Anxiety or Extrinsic Goal Orientation significantly improved the scale's consistency. However, Hypothesis 1 is partially supported because when examining specific subscales, task value, control of learning beliefs, and self-efficacy emerged as significant predictors, suggesting that while the overall scale may not capture the nuanced effects of motivation, specific motivational factors are highly influential, the significance of specific motivational subscales underscoring the importance of examining these factors individually rather than as a composite scale.

Similar to the motivational strategies, the holistic *Learning Strategy Scale* did not show statistically significant effects on academic performance ($p > 0.05$) in the regression model. While the Learning Strategy Scale demonstrated a very good internal consistency (C. alpha = .845), its failure as a holistic predictor suggests that its effectiveness was diluted by aggregating diverse components. The scale combines fundamental cognitive strategies (like Rehearsal and Elaboration) with complex self-regulatory strategies. The strong effects of highly relevant, self-regulated strategies, such as effort regulation, metacognitive self-regulation, and help-seeking, were found to be significant predictors, demonstrating that certain learning strategies have a greater impact on academic performance than others. The holistic construct likely failed because the power of these strong predictors was obscured by averaging them with strategies that showed less direct predictive utility in the aggregate model.

This methodological decision to move from holistic scales to individual subscales was statistically justified. The initial model employing the holistic scales only achieved an overall prediction accuracy of 46.7%. In sharp contrast, the second analysis utilizing the individual subscales was

statistically significant (χ^2 (48) = 124.285, $p < .001$) and substantially improved the model's predictive capability, achieving a high overall prediction accuracy of 58.7%. These findings demonstrate that the mechanisms influencing academic success are granular, determined by specific beliefs (e.g., self-efficacy, task value) and self-regulatory strategies (e.g., effort regulation), rather than by generalized composite scores that suffer from either low reliability or dilution effects.

The frequency of study programs (full-time vs. hybrid) emerged as a significant effect on academic performance, partially supporting Hypothesis 3: Study program frequency significantly influences academic performance among lower-performing students (below 6.99 and 7.00–7.99) but not those in the mid-range category (8.00–8.99). This suggests that the distinct structural characteristics of these programs differentially impact students depending on their baseline academic skills or external circumstances. Hybrid programs inherently place a greater burden of responsibility on the student, a shift that is likely more challenging for those already struggling academically. Therefore, lower-performing students (those below 8.00) may lack the intrinsic self-regulation or effort regulation strategies needed to manage this greater proportion of unsupervised individual study time effectively.

Moreover, students opting for hybrid/part-time study are often constrained by external responsibilities that directly interfere with the time and effort they can dedicate to complex academic tasks, factors that disproportionately impact those who are already struggling. Our results showed that while mid-range students (8.00–8.99) may possess sufficient effort regulation (consistency in activity and persistence in challenging tasks) or strong foundational abilities to maintain their grades despite the external pressures, the added strain from these factors, combined with the necessity for self-directed learning in a hybrid format, may push lower-performing students into significantly poorer academic results.

Studies related to our findings have shown that students' perceptions of assessment tasks, including congruence with learning goals and authenticity, directly affect self-efficacy and indirectly impact it through task value (Alkharusi et al., 2013). Expectancy-value theory posits that students' expectations for success and task values are critical for motivation and academic outcomes (Rosenzweig et al., 2019). Task values encompass interest, perceived importance, and perceived utility, which are positively related to ability perceptions and negatively correlated with perceptions of task difficulty (Eccles & Wigfield, 1995). Furthermore, the results indicate that students' beliefs about their control over learning outcomes and their confidence in

their abilities predict their level of effort, persistence, and use of learning strategies, which in turn influence their academic achievement (Şen, 2016).

From a practical perspective, these findings suggest that interventions aimed at enhancing academic performance should focus on helping students recognize the relevance and importance of academic tasks, building students' confidence in their ability to succeed, encouraging the use of effective learning strategies such as effort regulation, metacognitive self-regulation, and help-seeking, recognizing the unique challenges and needs of students in different study programs (full-time vs. hybrid).

Practical implications

The findings have several practical implications for educators and policymakers: (a) educators should analyze students' learning and motivational strategies to identify areas for improvement and provide feedback; (b) implementing career counseling programs that can help students align their academic tasks with their long-term goals, thereby enhancing their perception of task value and relevance; (c) continuous monitoring of students' learning processes and providing ongoing support can foster the development of self-efficacy, control beliefs, and effective learning strategies.

Limitations

The study's limitations relate to translating questionnaire items into Romanian and the cultural context. The number of cases analyzed, the heterogeneity of the student population, and the possible distortions introduced by local cultural factors may reduce the generalizability of the findings.

A significant limitation relates to the internal consistency of the Motivation Scale when used as an aggregate measure. The calculated Cronbach's alpha coefficient was .631, indicating questionable consistency. This low reliability suggests that the holistic Motivation Scale may not function as a cohesive, unified construct, thus introducing potential measurement error. Indeed, we observed that deleting the items related to Test Anxiety or Extrinsic Goal Orientation would significantly improve the alpha coefficient (to .796 and .825, respectively). This suggests that the aggregate score failed to reliably capture the variance in motivational strategies, which led to the lack of statistical significance observed in the initial regression model.

We also screened for multicollinearity using Variance Inflation Factors (VIFs). While most variables met the recommended threshold (VIF

< 3), the Task Value subscale registered a VIF of 3.173. Although this value only marginally exceeded the conventional threshold and was deemed acceptable, it indicates a potential for high correlation between Task Value and other predictors. This suggests that the coefficient estimates for Task Value should be interpreted cautiously, as interdependence among predictors might affect the stability of the regression model coefficients.

The analytical approach involved two stages. When the initial regression model using the holistic scales failed to predict academic performance significantly, providing "no support for Hypotheses 1 and 2", we proceeded to an analysis using the individual subscales. This shift means that the resulting significant findings derived from the subscales (e.g., self-efficacy, effort regulation) constitute an exploratory, post-hoc analysis aimed at identifying granular predictors. These findings, while highly informative (as evidenced by the model precision improvement to 58.7%), should be interpreted with caution. The specific combination of significant subscales requires independent replication in future studies to confirm their predictive stability and generalizability.

Finally, the study also shares common limitations, including the reliance on self-reported data, the possible distortions introduced by local cultural factors, and the acknowledgement that significantly correlated variables were neglected (such as age or university), with model error representing more than 40%.

Statement on the Use of AI Tools | *Artificial intelligence tools (Elicit 1.3, NotebookLM Plus - powered by Google Gemini 2.0, Claude Opus 4.1 and ChatGPT 4.1) were used to support the manuscript writing process. Specifically, they assisted in identifying and organizing relevant literature and analyzing selected studies, and in improving the clarity of the text. No AI tools were used for data analysis or during the research process.*
The authors take full responsibility for the design, analysis, interpretation, and conclusions of this work.

Appendix

Table 9. Parameter Estimates

	Media_numeric[a]	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
sub 6,99	Intercept	-1659.705	1240642.587	.000	1	.999			
	M1_Intrinsic.Goal.Orientation	-30.424	253659.978	.000	1	1.000	6.127E-14	.000	.[b]
	M2_Extrinsic.Goal.Orientation	206.404	317902.092	.000	1	.999	4.365E+89	.000	.[b]
	M3_Task.Value	-601.851	327276.188	.000	1	.999	4.165E-262	.000	.[b]
	M4_Control.of.Learning.Beliefs	214.251	185912.131	.000	1	.999	1.117E+93	.000	.[b]
	M5_Self_Efficacy.for.Learning. and.Achievement	-12.618	70572.830	.000	1	1.000	3.312E-6	.000	.[b]
	M6_Test.Anxiety	193.870	142787.666	.000	1	.999	1.573E+84	.000	.[b]
	Ls1_Rehearsal	13.353	158266.104	.000	1	1.000	629688.675	.000	.[b]
	Ls2_Elaboration	46.504	399065.539	.000	1	1.000	157238913750067540000.000	.000	.[b]
	Ls3_Organization	-563.905	287313.994	.000	1	.998	1.257E-245	.000	.[b]
	Ls4_Critical.Thinking	59.222	80163.804	.000	1	.999	52455463825060610000000000.000	.000	.[b]
	Ls5_Metacognitive.Self_Regulation	441.494	280583.916	.000	1	.999	5.477E+191	.000	.[b]
	Ls6_Time.and.Study.Environment.Management	73.754	279272.221	.000	1	1.000	10739942096178568000000000000000.000	.000	.[b]
	Ls7_Effort.Regulation	.184	157967.035	.000	1	1.000	1.202	.000	.[b]
	Ls8_Peer.Learning	118.654	151780.487	.000	1	.999	3.394E+51	.000	.[b]
	Ls9_Help.Seeking	162.409	162234.571	.000	1	.999	3.414E+70	.000	.[b]
	[Full study program=0]	681.613	.000	.	1	.	1.049E+296	1.049E+296	1.049E+296
	[Full study program=1]	0[c]	.	.	0	.	.	.	.

7,00 - 7,99	Intercept	5.123	2.582	3.936	1	.047			
	M1_Intrinsic.Goal.Orientation	1.037	.632	2.695	1	.101	2.821	.818	9.730
	M2_Extrinsic.Goal.Orientation	.816	.422	3.737	1	.053	2.262	.989	5.177
	M3_Task.Value	.639	.720	.788	1	.375	1.895	.462	7.769
	M4_Control.of.Learning.Beliefs	-1.065	.540	3.885	1	**.049**	**.345**	.120	.994
	M5_Self_Efficacy.for.Learning.and.Achievement	-1.681	.628	7.159	1	**.007**	**.186**	.054	.638
	M6_Test.Anxiety	-.519	.288	3.244	1	.072	.595	.338	1.047
	Ls1_Rehearsal	.341	.483	.498	1	.480	1.406	.546	3.622
	Ls2_Elaboration	-.863	.592	2.123	1	.145	.422	.132	1.347
	Ls3_Organization	-.210	.468	.202	1	.653	.810	.324	2.028
	Ls4_Critical.Thinking	.119	.449	.070	1	.791	1.126	.467	2.715
	Ls5_Metacognitive.Self_Regulation	.700	.762	.844	1	.358	2.013	.453	8.957
	Ls6_Time.and.Study.Environment.Management	-.614	.499	1.515	1	.218	.541	.204	1.438
	Ls7_Effort.Regulation	-.379	.479	.626	1	.429	.685	.268	1.751
	Ls8_Peer.Learning	.008	.372	.000	1	.983	1.008	.487	2.088
	Ls9_Help.Seeking	-.129	.421	.095	1	.758	.879	.385	2.005
	[Full study program=0]	.570	.551	1.071	1	.301	1.769	.601	5.211
	[Full study program=1]	0[c]	.	.	0	.	.	.	.
8,00 - 8,99	Intercept	3.759	1.834	4.204	1	.040			
	M1_Intrinsic.Goal.Orientation	.146	.439	.111	1	.739	1.158	.490	2.737
	M2_Extrinsic.Goal.Orientation	-.003	.252	.000	1	.992	.997	.608	1.635
	M3_Task.Value	1.104	.507	4.733	1	**.030**	**3.015**	1.116	8.149
	M4_Control.of.Learning.Beliefs	-.435	.376	1.338	1	.247	.648	.310	1.352
	M5_Self_Efficacy.for.Learning.and.Achievement	-1.347	.449	9.000	1	**.003**	**.260**	.108	.627
	M6_Test.Anxiety	-.219	.193	1.291	1	.256	.803	.550	1.172

	Ls1_Rehearsal	.493	.312	2.486	1	.115	1.637	.887	3.020
	Ls2_Elaboration	-.022	.389	.003	1	.955	.978	.457	2.095
	Ls3_Organization	.400	.330	1.474	1	.225	1.492	.782	2.849
	Ls4_Critical.Thinking	-.302	.308	.960	1	.327	.739	.404	1.353
	Ls5_Metacognitive.Self_Regulation	-.339	.515	.434	1	.510	.712	.259	1.956
	Ls6_Time.and.Study.Environment.Management	.041	.343	.015	1	.904	1.042	.533	2.040
	Ls7_Effort.Regulation	-.843	.329	6.543	1	**.011**	**.431**	.226	.821
	Ls8_Peer.Learning	.261	.262	.992	1	.319	1.298	.777	2.169
	Ls9_Help.Seeking	-.175	.285	.377	1	.539	.840	.481	1.467
	[Full study program=0]	.146	.395	.137	1	.712	1.157	.534	2.510
	[Full study program=1]	0[c]	.	.	0	.	.	.	.

a. The reference category is: 9,00 - 10,00.
b. Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.
c. This parameter is set to zero because it is redundant.

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