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Predictori ai implicării în activitatea academică în învăţământul superior: o analiză de regresie liniară multiplă ierarhică

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PREDICTORS OF ACADEMIC WORK ENGAGEMENT IN HIGHER EDUCATION: A HIERARCHICAL MULTIPLE LINEAR REGRESSION ANALYSIS

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Abstract
A student's level of academic work engagement is a key predictor of their retention in higher education (HE) and their commitment to lifelong learning. While existing research frequently identifies motivation as the main driver of this engagement,

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other factors – such as students' specific learning strategies and situational interests – have received limited empirical attention. Using a non-experimental two-wave longitudinal design, we examined the extent to which academic motivation, situational interest, and learning approaches predict students' academic work engagement over the course of a semester. Data were collected across two waves from a volunteer sample of 129 bachelor's students, comprising 86.8% females with an average age of 21.36 years. For the data analysis, we used a hierarchical multiple linear regression analysis. Our results indicated that prior engagement (step 1) was the strongest predictor of future academic work engagement. While early stages of the model (steps 2 and 3) showed intrinsic motivation for stimulation as a significant factor, the final model (step 4) revealed the deep learning approach as the dominant predictor, largely diminishing the impact of motivation. Also, situational interest (step 3) did not significantly predict engagement outcomes. Present findings indicate that, while motivation is important, how a student processes information (i.e., a deep learning approach) might be a stronger predictor for learning engagement in HE than students' initial levels of learning motivation. Therefore, teachers might benefit more from integrating deep learning strategies, rather than relying solely on motivational interventions. Practical implications for HE teachers and research directions are further detailed in the manuscript.

Keywords: academic motivation, academic work engagement, learning approach, situational interest.

Rezumat

Nivelul de angajament al studenţilor în activitatea academică este un indicator esenţial al perseverenţei lor în învăţământul superior şi în învăţarea pe tot parcursul vieţii. Deşi cercetările existente identifică frecvent motivaţia ca fiind principalul motor al acestei implicări, alţi factori – precum strategiile specifice de învăţare ale studenţilor şi interesul situaţional – au primit o atenţie empirică limitată. Folosind un design longitudinal neexperimental în două etape, am analizat măsura în care motivaţia academică, interesul situaţional şi abordările învăţării preferate de studenţi prezic angajamentul academic al acestora pe parcursul unui semestru. Sondajul a fost completat voluntar de 129 de studenţi la nivel de licenţă (86,8% femei, vârsta medie de 21.36). Pentru analiza datelor, am utilizat o regresie liniară multiplă în patru paşi. Rezultatele noastre au indicat faptul că nivelul anterior de angajament al studenţilor în activitatea academică (pasul 1) a fost cel mai puternic predictor pentru nivelul lor viitor de angajament. În timp ce stadiile iniţiale ale modelului (paşii 2 şi 3) au arătat motivaţia intrinsecă pentru stimulare ca fiind un factor predictiv semnificativ, modelul final (pasul 4) a relevat abordarea învăţării de profunzime drept predictorul dominant, diminuând în mare măsură impactul motivaţiei. De asemenea, interesul situaţional *(pasul 3) nu a prezis în mod semnificativ rezultatele angajamentului. Constatările actuale indică faptul că, deşi motivaţia este importantă, modul în care un student procesează informaţiile (adică o abordare de învăţare de profunzime) ar putea fi un factor predictiv mai puternic pentru angajamentul în învăţare în învăţământul superior decât nivelurile iniţiale de motivaţie pentru învăţare ale studenţilor. Prin urmare, profesorii ar putea să acorde mai multă prioritate promovării strategiilor de învăţare profundă, în loc să se bazeze exclusiv pe intervenţii motivaţionale. Implicaţiile practice pentru profesorii din învăţământul superior şi direcţiile de cercetare sunt detaliate în continuare în manuscris.*

Cuvinte-cheie: *abordarea învăţării, angajament în activitatea academică, interes situaţional, motivaţie academică.*

1. Introduction

In the modern university landscape, shifts toward blended and student-centered learning models (Shehata et al., 2025) have placed unprecedented importance on student autonomy and self-regulation. While these models aim to foster independence, the quality of the learning experience is increasingly dependent on the student's academic work engagement. The use of artificial intelligence in the academic environment has also brought challenges in relation to how new information is acquired and the quality of the materials produced by students (Cheng et al., 2022). These approaches promote the development of student autonomy, making them responsible for their own learning process, but education is at a turning point where the "humanity" of the personalized learning process must be protected (Shehata et al., 2025). Therefore, understanding the psychological mechanisms – beyond just initial motivation – that sustain student effort over time is essential for academic persistence.

In Romania, the challenge of academic persistence is particularly acute; while general statistics often highlight an 'early leaver' rate[1] of 16.8% (Eurostat, 2024), data from the 2022/2023 academic year reveal a university-specific annual dropout rate of 9.9% (Ministry of Education, 2023). These figures become even more concerning when analyzed by study format, with non-completion risks rising to 18.2% in distance learning programs (Ministry of Education, 2024). This vulnerability underscores the critical role of academic engagement as a fundamental predictor of persistence in higher education (Kuh et al., 2008). Beyond its inverse relationship with dropout rates (Pérez et al., 2021; Skinner, 2023), high engagement serves as a vital indicator of academic performance, the cultivation of lifelong learning skills, and enhanced graduate employability (Kahu, 2013).

Although previous research has extensively explored the relationship between academic engagement and student motivation (Appleton et al., 2008; Reeve et al., 2025; Skinner et al., 2008), studies that integrate situational interest into this equation are rare and, in most cases, treat these variables separately (Renninger & Hidi, 2015). Integrating context and study environment into this relationship is an attempt to interconnect these dimensions (cognitive, affective, and behavioral) (Renninger & Bachrach, 2015). While motivation explains students' reasons for acting ("why am I doing it"), situational interest describes the immediate appeal of the task, triggered in a specific learning environment ("what grabs my attention in the classroom"). Beyond these limitations, there is a significant gap in the literature regarding the predictive relationship between students' learning approach strategies and the development of long-term academic engagement.

To address these theoretical and practical limitations, the main goal of this study is to analyze the extent to which academic motivation, situational interest, and students' preferred learning approach predict their engagement in academic work over the course of a semester. Using a longitudinal design with two measurement points, the research aims to capture the temporal variation of these variables among undergraduate students at the West University of Timişoara (WUT). Additionally, the longitudinal approach allows for autoregressive control of initial engagement in academic work, thus providing a more rigorous understanding of predictive relationships.

1.1. Theoretical framework

1.1.1. *Academic work engagement*

Due to its complexity, academic engagement is considered in the literature to be a multidimensional construct; consequently, identifying a single, universally accepted definition remains a challenge (Wong & Liem, 2022). Academic engagement is a dynamic system of student participation, investment, and dedication to educational activities, playing a decisive role in the quality of the learning experience and long-term success (Chen et al., 2023).

To measure the effort invested by students, educational researchers have adapted the "work engagement" model from organizational psychology to the university context (Salmela-Aro & Upadyaya, 2012). From this perspective, academic work engagement (AWE) is structured around three central dimensions: vigor (high levels of energy and the desire to persevere and invest time in a task), dedication (a strong sense of involvement characterized by enthusiasm, pride, significance, and challenge), and absorption (a state of complete concentration and captivation while working, often accompanied by a distorted perception of time, which appears to pass more quickly).

Out of routine or conformity, students may engage in certain activities even in the absence of intrinsic motivation or high interest (Renninger & Hidi, 2015). Given that the central objective of this research is to understand the quality and depth of how students relate to their learning activities, the use of AWE allows for a differentiation between simply "checking off" tasks and a student's authentic cognitive and emotional involvement. However, the amount of energy and concentration a student allocates to academic tasks is fundamentally dictated by their type of academic motivation. While some forms of motivation foster long-term commitment, others are limited to fulfilling minimum requirements focused on external performance indicators.

1.1.2. *Academic motivation*

The close relationship between student motivation and academic engagement – the latter often seen as the behavioral manifestation of the former (Skinner et al., 2008) – has been extensively documented (Appleton et al., 2008; Reeve et al., 2025). Motivation and task value are the primary internal factors that correlate positively with engagement (Myint & Khaing, 2020), while gender, teaching style, and grades act as external variables. Essentially, academic engagement is determined to a greater extent by the individual and motivational characteristics of the student, rather than structural factors or the characteristics of the university (Perkmann et al., 2021).

In academia, students' academic motivation refers to their desire to find the most appropriate cognitive strategies to achieve their learning and performance goals (Cotruş et al., 2014). The most robust explanatory framework for this learning process is Self-Determination Theory (SDT; Ryan & Deci, 2017). According to SDT, the quality of motivation is determined by the extent to which the academic environment satisfies three basic psychological needs: autonomy, competence, and relatedness. Depending on the level of satisfaction of these needs, motivation is conceptualized as *autonomous motivation* (engaging in a task out of genuine interest, enjoyment, or personal value, encompassing intrinsic and identified regulation) and *controlled motivation* (engaging due to internal or external pressures, such as guilt, pride, or rewards, encompassing introjected and external regulation), alongside *amotivation* (the complete lack of intention to act).

Howard and his colleagues (2021), in their meta-analysis, examined the relationship between these types of motivation and academic outcomes. Autonomous forms of motivation – particularly intrinsic motivation – are the strongest positive predictors of academic work engagement and adaptive learning strategies. While controlled motivation may temporarily increase invested effort, it is strongly correlated with performance-oriented learning and anxiety. Amotivation and purely extrinsic forms are consistently associated with frustration, burnout, and lower levels of academic engagement (Myint & Khaing, 2020). Therefore, understanding a student's placement on this motivational continuum is essential for predicting their sustained engagement over a semester. However, if the specific academic tasks assigned by the teacher lack immediate relevance, even the most autonomously motivated student may find it difficult to engage in the task. This is why *situational interest* was chosen as a more context-sensitive predictor in this study.

1.1.3. *Situational interest*

Although interest generates motivation and commitment, the relationship is not valid in the opposite direction: a student may be motivated and involved in a task (e.g., out of a desire to receive a scholarship) without experiencing a state of genuine interest (Renninger & Hidi, 2015). Thus, interest represents not only a person's immediate psychological state during a task, but also a cognitive and affective disposition that fuels the desire to voluntarily re-engage in an activity over time (Tang et al., 2022).

Interest, as a subjective learning experience, can be triggered by an external situational trigger or by a well-developed individual interest (Tang et al., 2022). Therefore, the concept of interest is divided into two (Shin & Kim, 2019): *situational interest* – aroused by a situational trigger, which persists only as long as the task is perceived as relevant or meaningful; and *individual interest* – a relatively stable trait of the individual, characterized by a predisposition to re-engage with particular content over time. In this study, we decided to discuss only situational interest, as it is much easier to shape through external and contextual factors in the learning environment.

Once the student is energized by their state of interest, the way they approach learning can define their sustained academic engagement. An interested student is unlikely to settle for rote memorization, tending instead toward a more profound interaction with the learning content. Therefore, the learning approach is not merely a study method, but the cognitive mechanism through which a state of interest can be translated into durable academic results and sustained engagement.

1.1.4. *Learning approach*

The development of interest depends on an optimal alignment between teaching methods and students' individual characteristics (Renninger & Hidi, 2015). A comprehensive understanding of academic performance requires moving beyond a focus on affective and motivational states (internal state) to include the specific cognitive strategies students employ to navigate their studies. In the university environment, this interface between educational stimuli and the internal assimilation process is best described through the lens of learning approaches.

An important role of education is to encourage students to choose a *deep learning approach* over a *surface approach* (Biggs, 1988). According to the literature, the two approaches are clearly differentiated by intention and process. Deep learning can be understood as the desire to complete a task or understand a concept in a meaningful way that activates higher-order cognitive processes, linking new information to prior knowledge. At the opposite end, the surface learning approach is characterized by minimal cognitive effort, but sufficient to complete the task required by the teacher in order to obtain a good grade or reward. Its presence indicates that there is a dysfunction in the teaching-learning-assessment process, regarding the teaching methods used or the assessment methods (Biggs et al., 2001). Thus, surface learning has an instrumental role and is not a mechanism for long-term acquisition, with deep learning strategies being preferred (Biggs, 1988).

Given that previous research indicates that intrinsic motivation favors the adoption of a deep learning approach (Bolkan et al., 2011) and that, simultaneously, autonomous forms of motivation are predictors of academic engagement (Howard et al., 2021), it becomes imperative to explore the entire relational chain. Therefore, we expect that the way students approach learning (the cognitive strategy chosen) will function as a linking mechanism and, in turn, represent a direct and significant predictor of students' level of engagement in academic work.

1.2. Hypothesis

Based on the theoretical information presented above, in this paper we propose the following research hypotheses:
Hypothesis 1: Baseline academic work engagement (T1) will positively and significantly predict end-of-semester academic work engagement (T2).
Hypothesis 2: Academic motivation (T1) will positively predict academic work engagement (T2), explaining significant incremental variance above and beyond the autoregressive effect of baseline engagement.
Hypothesis 3: Situational interest (T1) will positively predict academic work engagement (T2), contributing additional predictive value beyond both baseline engagement and academic motivation.
Hypothesis 4: A deep learning approach (T1) will positively predict academic

work engagement (T2), accounting for significant incremental variance beyond baseline engagement, academic motivation, and situational interest. Hypothesis 5: A surface approach to learning (T1) will negatively predict, or have no significant relationship with, academic work engagement (T2).

2. Methodology

2.1. Study design

This study has a longitudinal design, with two measurement points. The four variables measured in this research are the following: motivation to study, with seven sub-dimensions (intrinsic motivation (IM)-simple; IM-achievement-oriented; IM-for stimulation; extrinsic motivation (EM)-identification; EM-introjection; EM-external regulation, lack of motivation - amotivation), situational interest (triggered SI, maintained SI - value, maintained SI - feeling), students' preferred approach to learning (surface learning, deep learning), and academic work engagement (AWE).

2.2. Participants

The participants in this study are 129 students (86.8% female) enrolled in four different bachelor's degree programs at the West University of Timişoara, with an average age of 21.36 years (*SD* = 3.76, Min = 18, Max = 42). Most students were from the Faculty of Sociology and Psychology (*N* = 89), a field predominantly composed of females. A convenience sampling method was employed, as the questionnaires were administered with four teachers' consent at the beginning of their classes, from three different faculties (Table no. 1). Data collection followed a hybrid approach, combining in-person administration during lectures with online distribution via student communication channels. Their distribution by year of study, semester, faculty, and discipline can be found in Table no. 1.

Table no. 1. *Demographic variables of the participants (N = 129)*

Variables		N	%
Sex			
	Female	112	12.4%
	Male	16	86.8%
	Other	1	0.8%
Bachelor's year of study			
	First year	26	20.2%
	Second year	83	64.3%
	Third year	20	15.5%
Semester			
	1	42	32.6%
	2	87	67.4%
Faculty			
	Faculty of Law	1	0.8%
	Faculty of Economics and Business Administration	28	21.7%
	Faculty of Physics	11	8.5%
	Faculty of Sociology and Psychology	89	69%
Discipline			
	Accounting in the public sector	25	19.4%
	Diversity and interculturality among multinational organizations*	4	3.1%
	Electronics Laboratory	11	8.5%
	Research methodology in educational sciences	43	33.3%
	Primary and preschool education pedagogy	13	10.1%
	Sociology of religions	7	5.4%
	Curriculum theory and methodology	26	20.2%

Note. * = complementary cross-disciplinary discipline

2.3. Instruments

To measure students' academic work engagement, we used the 9-items *Utrecht Student Engagement Scale* (Schaufeli et al., 2006). This instrument measures three dimensions (vigor, dedication, and absorption) using a 7-point frequency scale ranging from *never* (0) to *always* (6). The scale showed high internal consistency for the total engagement score (α T1 = .92; α T2 = .91), as well as across its individual subscales at both time points (α from .82 to .89).

The *Academic Motivation Scale* (Vallerand et al., 1993, Romanian translation from Research Central, n.d) has 28 items divided in seven 4-item dimensions: three types of intrinsic motivation (to know, achievement orientation, for stimulation), three types of extrinsic motivation (identification, introjection, external regulation), and amotivation. Items are rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). The instrument demonstrated strong internal reliability across all dimensions at both T1 and T2 (α ranged from .81 to .91).

To measure students' situational interest (SI), we used the *Situational Interest Survey* (Linnenbrink-Garcia et al., 2010). Responses were recorded on a 7-point Likert scale ranging from *Not at all true for me* (1) to *Always true for me* (7). The survey assesses three dimensions: triggered situational interest, maintained situational interest-feeling, and maintained situational interest-value. Internal consistency was acceptable to excellent across all subscales for both data collection waves (α ranged from .70 to .91)

Students' learning strategies were evaluated using the 20-item Revised Two-Factor Study Process Questionnaire (R-SPQ-2F; Biggs et al., 2001), adapted for the Romanian population by Smarandache et al. (2022). Responses are scored on a 5-point Likert scale (1 = *very rarely true* to 5 = *almost always true*). The items are equally divided into two subdimensions: deep learning approach and surface learning approach. Both subscales demonstrated good reliability at both time points (á values ranged from .81 to .89).

2.4. Procedure

The 10–15-minute online questionnaire was administered via QuestionPro at the beginning of designated lectures using a projected QR code, following teacher's approval. Informed consent was obtained, and data confidentiality was maintained using a self-generated unique identification code (comprising specific characters from the participant's name, birth year, mother's name, and birthplace). We administered the questionnaire at the beginning and end of the first semester of the 2022–2023 academic year (T1 = 142, T2 = 70). Due to an insufficient number of data pairs, between the two time points, we opted to administer the questionnaire in the second semester as well, to a new cohort of students (T1 = 268, T2 = 172). Combining the two data collection periods, we obtained 390 completed responses in T1 and 242 in T2. Of these, by matching the unique codes (to ensure anonymity) across the two time points for the intra-individual analysis we obtained a final, usable sample of 129 data pairs that we included in this study.

3. Results

3.1. Preliminary analysis

First, we performed descriptive analyses to see the shape of the data distribution and the values of the central tendency indicators. Having two time points, we then performed a comparative analysis between T1 and T2, using t-tests for paired samples (Table no. 2), to see if there was any variation in the variables during the semester. According to standard benchmarks, we interpreted Cohen's *d* values of .20, .50, and .80 as small, medium, and large effect sizes. No significant differences were identified in the learning approach chosen by students and their commitment to academic work.

From the perspective of students' *academic motivation* to study, we reported three significant differences between the two measurement points (Table no. 2), reporting small and very small effects for the variables "IM – knowledge" ($t_{(128)} = 3.502, p < .01, d = .30$), "amotivation" ($t_{(128)} = 2.956, p < .01, d = .27$) and "EM – identification" ($t_{(128)} = 2.586, p < .05, d = .22$). For *situational interest* (SI), we identified two significant differences: "maintained SI – value" ($t_{(128)} = 2.273, p < .05, d = .22$) and "triggered SI" ($t_{(128)} = 2.346, p < .05, d = .20$), also having a small effect. The differences in the means of the variables mentioned show that students' interest and motivation were not as high in T2 as in T1, but the small effect (between .03 and .27) and large standard deviations (between .90 and 1.24) show us that the general tendency of students was to maintain their interest throughout the semester.

Table no. 2. *Comparative analysis between T_1 and T_2, conducted using paired samples t-tests (N =129)*

Variable	T_1			T_2			$t_{(128)}$	p	Cohen's d
	M		**SD**	**M**		**SD**			
1. IM_Knowledge	5.55		0.95	5.27		1.04	3.502	**.001**	.30
2. IM_Accomplishments	4.96		1.01	4.89		1.08	.820	.414	.07
3. IM_Stimulation	4.07		1.18	4.06		1.28	.064	.949	.01
4. EM_Identification	5.32		1.17	5.13		1.19	2.586	**.011**	.22
5. EM_Introjection	5.09		1.20	5.15		1.97	-.617	.538	.06
6. EM_External_Regulation	4.74		1.17	4.69		1.23	.663	.508	.05
7. Amotivation	5.97		1.20	5.72		1.24	2.956	**.004**	.27
8. Triggered SI	5.84		0.99	5.66		1.05	2.346	**.021**	.20
9. Maintained SI – Feeling	5.51		1.08	5.36		1.29	1.697	.092	.14
10. Maintained SI – Value	5.82		0.90	5.67		0.99	2.273	**.025**	.22
11. Deep Learning Approach	3.04		0.80	3.01		0.77	.707	.481	.05
12. Surface Learning Approach	2.39		0.70	2.44		0.77	-.990	.324	.08
13. Academic Work Engagement T1	4.61		1.04	4.53		0.99	1.175	.242	.12

Note**.** T_1 = Time 1, T_2 = Time 2, M = mean, SD = standard deviation, t = test indicator, Cohen's d = effect size, IM = intrinsic motivation, EM = extrinsic motivation, SI = situational interest.

Before performing the regression analysis, we checked whether the data we collected met the necessary assumptions. Thus, in both T1 and T2, the data distribution is symmetrical, and all predictor variables correlate with the AWE variables (Table no. 3). At the same time, there is no multicollinearity, an assumption verified by calculating the Variance Inflation Factor (VIF), with values ranging between 1 and 5 (Shrestha, 2020). All correlation values between variables are shown in Table no. 3. To measure the practical significance of the relationship, the coefficient of determination (r^2) was used to calculate the explained variance, with values of .01, .09, and .25 representing small, medium, and large effect sizes, respectively.

The strongest positive correlation of AWE in T1, with a large effect, is with the *deep learning approach* ($r_{(127)} = .749$, $r^2 = .56$, $p < .001$), followed by two other variables: *IM - stimulation* ($r_{(127)} = .622$, $r^2 = .38$, $p < .001$) and *IM-achievement* ($r_{(127)} = .611$, $r^2 = .37$, $p < .001$). In relation to situational interest, the strongest association between *AWE_T1* is with *maintained SI – feeling_T1* ($r_{(127)} = .564$, $r^2 = .32$, $p < .001$).

The strongest association of *AWE_T2* is with *AWE_T1* ($r_{(127)}$ = .752, r^2 = .57, p < .001), reporting a large effect. Of the variables used in the regression model, the higher values of association of *AWE_T2* are with *deep learning approach _T1* ($r_{(127)}$ = .667, r^2 = .44, p < .001) and with the motivational scales: *IM - stimulation* ($r_{(127)}$ = .587, r^2 = .34, p < .001) and *IM-achievement* ($r_{(127)}$ = .531, r^2 = .28, p < .001). *Maintained SI– feeling_T2* ($r_{(127)}$ = .588, r^2 = .35, p < .001) correlates with *AWE_T2* as well with a large effect size. More associations between variables can be found in Table no. 3.

Table no. 3. *Correlation values for all the analysed variables, on the two moments of data collection*

Variables	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. IMK_T1	5.55	0.95																									
2. IMK_T2	5.27	1.05	.605**																								
3. IMA_T1	4.96	1.01	.573**	.530**																							
4. IMA_T2	4.89	1.08	.438**	.757**	.620**																						
5. IMS_T1	4.07	1.18	.521**	.466**	.582**	.431**																					
6. IMS_T2	4.06	1.28	.468**	.748**	.534**	.721**	.650**																				
7. EMID_T1	5.32	1.17	.620**	.388**	.414**	.297**	.456**	.395**																			
8. EMID_T2	5.13	1.19	.564**	.585**	.328**	.468**	.298**	.544**	.735**																		
9. EMIJ_T1	5.09	1.20	.152	.208*	.624**	.444**	.463**	.349**	.254**	.096																	
10. EMIJ_T2	5.15	1.20	.287**	.529**	.586**	.702**	.348**	.534**	.320**	.345**	.653**																
11. EMER_T1	4.74	1.17	.305**	.307**	.437**	.342**	.466**	.392**	.613**	.438**	.561**	.409**															
12. EMER_T2	4.69	1.23	.344**	.522**	.422**	.465**	.343**	.521**	.488**	.594**	.363**	.482**	.701**														
13. AMT_T1	5.97	1.20	.701**	.568**	.433**	.360**	.392**	.403**	.488**	.495**	.055	.222*	.192*	.289**													
14. AMT_T2	5.72	1.24	.598**	.636**	.386**	.462**	.321**	.453**	.466**	.569**	.086	.294**	.195*	.400**	.697**												
15. SIT_T1	5.51	1.08	.688**	.574**	.371**	.357**	.350**	.445**	.438**	.511**	.013	.200*	.199*	.312**	.692**	.570**											
16. SIT_T2	5.36	1.29	.590**	.663**	.333**	.486**	.307**	.523**	.339**	.500**	.072	.267**	.176*	.289**	.592**	.697**	.668**										
17. SIMF_T1	5.82	0.90	.761**	.566**	.475**	.421**	.429**	.483**	.611**	.559**	.115	.289**	.293**	.345**	.683**	.577**	.710**	.594**									
18. SIMF_T2	5.67	0.99	.678**	.776**	.474**	.595**	.413**	.611**	.500**	.601**	.227**	.450**	.348**	.466**	.656**	.687**	.666**	.801**	.718**								
19. SIMV_T1	5.84	0.99	.728**	.524**	.458**	.354**	.361**	.407**	.651**	.575**	.057	.306**	.264**	.291**	.647**	.619**	.647**	.546**	.784**	.638**							
20. SIMV_T2	5.66	1.05	.615**	.708**	.341**	.482**	.298**	.552**	.530**	.718**	.103	.373**	.272**	.452**	.607**	.638**	.623**	.717**	.624**	.794**	.630**						
21. SLA_T1	2.39	0.70	-.386**	-.365**	-.268**	-.272**	-.278**	-.311**	-.308**	-.399**	-.032	-.098	-.061	-.137	-.452**	-.387**	-.402**	-.306**	-.503**	-.432**	-.315**	-.384**					
22.SLA_T2	2.44	0.77	-.384**	-.391**	-.259**	-.274**	-.287**	-.252**	-.272**	-.347**	-.029	-.086	-.001	-.094	-.391**	-.436**	-.328**	-.350**	-.442**	-.438**	-.327**	-.362**	.645**				
23. DLA_T1	3.04	0.80	.502**	.439**	.553**	.459**	.595**	.483**	.559**	.361**	.462**	.329**	.429**	.323**	.298**	.386**	.350**	.269**	.480**	.427**	.444**	.288**	-.231**	-.298**			
24. DLA_T2	3.01	0.77	.430**	.519**	.489**	.555**	.498**	.629**	.364**	.381**	.346**	.363**	.276**	.250**	.327**	.464**	.373**	.438**	.443**	.526**	.410**	.448**	-.294**	-.219*	.687**		
25. AWE_T1	4.65	0.99	.521**	.469**	.611**	.490**	.622**	.524**	.457**	.340**	.467**	.384**	.384**	.338**	.394**	.435**	.428**	.349**	.564**	.543**	.466**	.379**	-.371**	-.367**	.749**	.617**	
26. AWE_T2	4.54	0.95	.479**	.574**	.531**	.601**	.587**	.621**	.380**	.349**	.376**	.416**	.311**	.246**	.365**	.500**	.395**	.471**	.460**	.588**	.414**	.445**	-.304**	-.325**	.667**	.800**	.752**

Note. $^{**}p < .001$, $^{*}p < .05$; T1 = time-point 1, T2 = time-point 2, IMK = intrinsic motivation for knowledge, IMA = intrinsic motivation for achievement, IMS = intrinsic motivation for stimulation, EMID = extrinsic motivation for identification, EMIJ = extrinsic motivation for introjection, EMER = extrinsic motivation for external regulation, AMT = amotivation, SIT = triggered situational interest, SIMF = situational interest maintained by feeling, SIMV = situational interest maintained by value, SLA = surface learning approach, DLA = deep learning approach, AWE = academic work engagement.

3.2. Hierarchical multiple linear regression analysis

Table no. 4 presents the results of the hierarchical multiple linear regression analysis, which controlled for temporal effects by introducing AWE_T1 as a predictor of AWE_T2. The primary objective was to determine the predictive power of *academic motivation, situational interest,* and *learning approaches* regarding AWE_T2 over and above the autoregressive effect. These variables were introduced in successive steps to isolate their unique contributions to the variance in academic work engagement.

Table no. 4. *Hierarchical multiple linear regression analysis for Academic work engagement_T_2*

	Variable	B	ES B	ß	R^2	ΔR^2
Step 1						
	Constant	1.22	.26	.75	.566	**.566***
	T_1_AWE	.72	.06			
Step 2						
	Constant	.86	.41		.595	.029
	T_1_AWE	.57	.08	**.60***		
	IM_Knowledge	.06	.11	.06		
	IM_Accomplishments	.04	.10	.04		
	IM_Stimulation	.15	.07	**.17***		
	EM_Identification	-.01	.08	-.02		
	EM_Introjection	.00	.08	.00		
	EM_External_Regulation	-.03	.08	-.03		
	Amotivation	.01	.07	.01		
Step 3						
	Constant	.84	.46		.598	.003
	T_1_AWE	.58	.09	**.60***		
	IM_Knowledge	.05	.12	.05		
	IM_Accomplishments	.04	.10	.04		
	IM_Stimulation	.15	.07	**.18***		
	EM_Identification	-.02	.09	-.02		
	EM_Introjection	.01	.08	.01		
	EM_External_Regulation	-.03	.08	-.03		
	Amotivation	.00	.08	-.01		
	Triggered SI	.06	.09	.06		
	Maintained SI - feeling	-.08	.13	-.08		
	Maintained SI - value	.07	.11	.06		
Step 4						
	Constant	1.08	.63		.616	.018
	T_1_AWE	.46	.10	**.48***		
	IM_Knowledge	.03	.12	.03		
	IM_Accomplishments	.03	.10	.03		
	IM_Stimulation	.12	.07	.15		
	EM_Identification	-.08	.09	-.10		
	EM_Introjection	-.01	.08	-.01		
	EM_External_Regulation	.00	.08	.00		
	Amotivation	.02	.08	.03		
	Triggered SI	.05	.09	.05		
	Maintained SI - feeling	-.09	.13	-.08		
	Maintained SI - value	.07	.11	.07		
	Deep learning approach	.28	.12	**.23***		
	Surface learning approach	-.04	.10	-.03		

Note. *$p < .05$, B = unstandardised regression coefficient, ß = standardised Beta coefficient, ES B = standard error, ΔR^2 = R Square Change, IM = intrinsic motivation, EM = extrinsic motivation, SI = situational interest.

In the first step, baseline academic work engagement (T1_AWE) was entered to control for autoregressive effects. The model was statistically significant ($F_{(1, 127)} = 165.65, p < .001$), explaining 56.6% of the variance in end-of-semester engagement (T2_AWE, $R^2 = .57, p < .001$). This indicates a high degree of stability in student engagement over the course of the semester. Building on this autoregressive effect (57%), the other variables were introduced gradually in the analysis.

In Step 2, we introduced the eight dimensions of *academic motivation* (AM) into the model ($F_{(8, 120)} = 9.37, p < .001$). While the overall model remained significant, the motivational block did not explain a significant amount of incremental variance ($\Delta R^2 = .027$, $p > .05$). Within this block, intrinsic motivation (IM) to experience stimulation was the only significant predictor (ß = .17, $p < .05$), uniquely contributing to the model when controlling for baseline engagement.

In Step 3, situational interest variables were added. The inclusion of this block did not result in a significant increase in explained variance, ($\Delta R^2 = .003$, $p > .05$). This suggests that situational interest does not serve as a unique predictor of T2_AWE when accounting for prior engagement and motivation. Notably*, IM to experience stimulation* maintained its significant predictive value (ß = .18, $p < .05$).

In the final step, by adding the learning approaches, the introduced variance is not significant at the level of the regression model ($F_{(13, 115)} = 14.17$) and the IM - to experience stimulation is no longer significant. Although the incremental variance for the block was not statistically significant ($\Delta R^2 = .018, p > .05$), the *deep learning approach* emerged as a significant positive predictor (ß = .23, $p < .05$). Concurrently, IM to experience stimulation dropped below the significance threshold (ß = .12, $p < .05$), suggesting that the adoption of deep cognitive strategies may supersede the influence of initial intrinsic motivation on long-term engagement.

4. Discussions

In this study, academic work engagement was analyzed as a behavior defined by persistence over time (Kuh et al., 2008) – the consistent effort applied to complete academic tasks. We examined the engagement levels of WUT students at the beginning and end of a semester, controlling for the autoregressive effect (the prediction of future values based on prior values). Accounting for autoregression is crucial as it determines whether the variance over time is attributable to the predictors or to the inherent stability of the construct. Furthermore, by introducing a time period between measurements, we reduced the risk of common method bias (Podsakoff et al., 2003), which often occurs when dependent and independent variables are measured simultaneously using the same method. Consequently, this longitudinal design provides higher empirical credibility than a cross-sectional approach. Given that the mean variations between T1 and T2 were minimal with small effect sizes, the predictive analysis provides significant added value.

Academic engagement at the beginning of the semester predicted 57% of the variance in engagement at the end of the semester. While literature suggests that motivation – particularly intrinsic, identified, and amotivation – is a primary predictor of engagement (Howard et al., 2021), our findings indicate that intrinsic motivation was the sole motivational predictor of academic work engagement. These results do not contradict previous research reported by Howard et al. (2021) but rather refine the explanation of the variation between these concepts. Even if the need for autonomy is secondary to the need for competence in the educational field (Bureau et al., 2022), promoting motivation that responds to the need for autonomy (intrinsic and internalized) is correlated with better academic results than controlled motivation (external and introjected). The reasons students engage in learning are deeply rooted in their enjoyment and interest (Bureau et al., 2022), which explains why intrinsic motivation to seek stimulation significantly predicted engagement. Although interest is different from motivation (Renninger & Hidi, 2015), it is still part of the motivational process. Therefore, with high association values between concepts, it is possible that the effect of the motivational variable to overshadow the effect of situational interest.

A novelty in studies seeking to identify potential predictors of student engagement in academic work is the introduction of the *learning approach* chosen by students into the prediction model. Although students with high levels of motivation and self-esteem have higher levels of academic engagement (Myint & Khaing, 2020), understanding the three dimensions of engagement (vigor, dedication, and absorption) requires a consideration of how students process information. When *learning approaches* were introduced alongside other variables, *deep learning* emerged as the sole significant predictor of *academic work engagement*, effectively accounting for the variance otherwise attributed to *intrinsic motivation or situational interest*.

This suggests that while *motivation* and *interest* are essential for initiating the learning process, they are not sufficient for sustaining engagement without deep cognitive processing. Deep learners adapt and meaningfully integrate new acquisitions into their cognitive schemas, to reach the levels of absorption and effort necessary for long-term persistence (Biggs, 1988). Their objective is comprehension rather than memorization. Since *intrinsic motivation* correlates most strongly with *deep learning* (Howard et al., 2021), it follows that when students are intellectually stimulated, they adopt this strategy (Bolkan et al., 2011). This active, meaningful learning behavior ultimately accounts for the variance that might otherwise be attributed independently to motivation or situational interest. Therefore, the statistical evidence suggests that the students' learning approach likely acts as a mediator in the relationship between autonomous motivation and academic work engagement.

4.1. Limitations

Several limitations should be considered when interpreting the findings of this study. First, the data were collected through self-reporting, which possess a lower degree of reliability. Furthermore, absenteeism is higher at the end of the semester. Therefore, it is highly likely that those who attended the final classes and completed the questionnaires were already more engaged in their academic work (selection bias).

Additionally, the use of convenience sampling led to an unbalanced distribution between students in the humanities (with an overrepresentation of female students) and those in the natural sciences, which limits the generalizability of these results across the entire university. Because many participants were drawn from the same department, shared teaching methods may have acted as unmeasured confounding variables. It is well documented that the teaching approach chosen by the teacher is closely related to their students' learning approaches (Trigwell & Prosser, 2020) and interest (Rotgans & Schmidt, 2011). Consequently, future research should explicitly integrate and control for teachers' instructional approaches to provide a more comprehensive picture of the learning environment.

Finally, there are methodological considerations regarding the specific measurements used. Although calculating the variance inflation factor ruled out strict multicollinearity, the notably strong correlations between motivational variables and situational interest suggest a conceptual overlap that may have influenced the predictive analysis. Furthermore, the multidimensional complexity of the applied instruments, which feature numerous distinct subscales, prevented the calculation of a single, integrated total score. To address this in future studies, researchers might seek out other instruments.

4.2. Implications

Although a student's prior level of academic engagement is the strongest predictor of their future engagement, the results suggest that AWE can be significantly enhanced by fostering intrinsic motivation – specifically the drive to experience stimulation – and a deep learning approach. Universities must move beyond simply monitoring student motivation and begin actively fostering the cognitive mechanisms that drive persistence. Since a deep learning approach emerged as the critical link to sustained engagement, designing a curriculum that prioritizes student-centered activities, that demand synthesis and critical thinking, in high-challenge environments is essential. Because initial engagement is such a strong predictor of future effort, early-semester interventions are essential to equip students with deep-processing tools like concept mapping before their interest naturally wanes. Ultimately, by shifting the pedagogical focus from the "why" of learning (motivation) to the "how" (deep strategies), educators can help students to maintain vigor and absorption throughout the academic year.

Author Note

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Note

[1] The percentage of the population aged 18–24 having attained at most a lower secondary education and not being involved in further education or training (Eurostat, 2024).

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