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VALIDATING A DEEP LEARNING MODEL: THE NEXUS OF SELF-REGULATION STRATEGIES AND STUDENT WELL-BEING

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Abstract

This study was principally focused on verifying the suitability of the Deep Learning Strategies Questionnaire for Romanian academic environments and examining the interrelations among deep learning strategies, self-efficacy, subjective well-being, and academic performance. Utilizing a correlational-cross-sectional approach, the research involved 130 university students from various Romanian institutions. Data gathering was conducted via an extensive multidimensional questionnaire, which assessed components such as deep learning strategies, perceived self-efficacy, subjective well-being, and academic performance indicators. The methodological process included extensive collaboration with several higher education institutions for participant recruitment. The data analysis was carried out using JASP version 0.18.1, which combined descriptive and inferential statistical approaches with structural equation modeling. The research aimed to endorse a theoretical model that interconnects deep learning self-regulation strategies with elements like student well-being, perceived self-efficacy, and their collective influence on academic achievement. Notably, the exploratory factor analysis revealed the presence of five distinct factors, an enhancement from the four factors identified in the original model, providing a more comprehensive understanding of deep learning strategies. Furthermore, the hierarchical model related to deep learning strategies exhibited strong congruence. The study's instruments demonstrated robust reliability and validity, as evidenced by internal consistency metrics ranging from acceptable to high levels. This substantiates the efficacy of these scales in evaluating a broad range of learning strategies in an educational setting.

Keywords: *deep learning strategies questionnaire; self-regulated learning; student well-being; self-efficacy; academic performance*

1. Introduction

During a period marked by unparalleled challenges in higher education, exacerbated by the COVID-19 pandemic, the intricate aspects of student learning demand heightened attention and understanding. This research article contributes to the scholarly conversation in higher education, focusing on the intersection of self-regulated learning strategies with factors like self-efficacy and well-being, and their collective impact on academic performance. Central to this study is the investigation of the Deep Learning Strategies Model within the context of Romanian higher education.

The study is driven by two research objectives. The first objective is a validation of the Deep Learning Strategies Questionnaire, developed by Panadero et al. (2021), targeting Romanian students. This validation process is pivotal in verifying the questionnaire's suitability and effectiveness within a distinct cultural and educational milieu. The second objective is an in-depth analysis of how deep learning strategies are interwoven with three key dimensions essential to learning in higher education: self-efficacy, subjective well-being, and academic achievement.

1.1. Conceptualization of Self-regulated learning

In the realm of higher education, a substantial body of research has been dedicated to exploring not just the content of student learning, but also the tactics, the methodologies, and processes underlying it (Ellis * et al. 2004; Martínez Fernández et al. 2016; Shum et al. 2023; Trigwell, Prosser, and Waterhouse 1999; Vermunt and Vermetten 2004; Winne 2022). Historically, student learning has been conceptualized as a quantitative enhancement, predominantly centered around the accumulation of facts and procedural knowledge (Bransford, Brown, & Cocking, 2000). However, over the last thirty years, a paradigm shift has been observed in higher education, steering towards a more developmental understanding of learning. This shift is anchored in four fundamental elements: achievement goals, self-efficacy beliefs, self-regulation, and learning strategies, with a multitude of studies underscoring the intricate interplay among these components (Bouffard et al. 2005; Mega, Ronconi, and De Beni 2014; Neuville, Frenay, and Bourgeois 2007; Nückles, Hübner, and Renkl 2009; Panadero 2017). To align with this evolving perspective, our approach is grounded in the phenomenography tradition, particularly in the context of students' approaches to learning (SAL). According to this framework, students engage with learning tasks from either a surface or deep approach (Biggs, Kember, and Leung 2001), with more recent categorizations differentiating these approaches into fragmented and cohesive types (Ellis and Calvo 2006; Martínez Fernández et al. 2016). Initial efforts to define the concept of self-regulated learning (SRL) emerged in the late 1980s, spearheaded by scholars such as Zimmerman and Boekaerts. These early models of SRL identified various processes internal to the individual, highlighting the roles of (meta)cognitive, motivational, and emotional components in the regulation of learning. Self-regulated learning represents a proactive process wherein learners leverage their cognitive and physical capabilities to develop skills relevant to specific tasks (Smelser and Baltes 2001; Winne 2022). This approach encompasses a range of metacognitive, motivational, and behavioral activities initiated by individuals for the purpose of acquiring knowledge and skills (Bransen et al. 2022; Panadero 2017; Zimmerman 2000). These activities include, but are not limited to, setting goals, planning, employing various learning strategies, self-reinforcement, self-monitoring, and self-guidance. Furthermore, self-regulation in learning transcends mere cognitive actions; it also involves tangible behavioral actions. Examples of these actions are choosing, altering, or creating environments conducive to learning, as well as actively seeking social assistance when needed (Bransen et al. 2022; Mega, Ronconi, and De Beni 2014; Neuville, Frenay, and Bourgeois 2007). Importantly, self-regulation is not confined to solitary learning endeavors. It also encompasses collaborative learning scenarios, where achieving personal goals is contingent upon the concerted efforts of multiple individuals (Allal 2020; Bransen et al. 2022; Schunk 2011). This aspect of self-regulation highlights its adaptability to both individual and collective learning contexts.

1.2. Self-regulated learning strategies

In this paper, we explore various self-regulated learning strategies that enhance the learning process in higher education, focusing on explicit regulation, narrative and visual synthesis, in-depth information processing, and social adjustment in learning (Panadero 2017; Panadero et al. 2021).

Explicit Regulation Strategies. According to Panadero (2017), most models divide the regulation process into three cyclical phases: preparation (including task analysis and planning), performance execution (where the task is carried out while monitoring progress), and evaluation (where students assess their results). Each phase encompasses specific sub-processes of regulation. However, some of these are less "visible" and therefore harder to regulate. For instance, during the preparation phase, numerous motivational sub-processes occur in microseconds, often escaping students' conscious awareness. Consequently, our focus is on explicit strategies pertinent to each of these three main phases, which are comprehensive and clearly understood by students.

Narrative and Visual Synthesis Strategies. Cognitive psychology research asserts that students must process, understand, and store information in their memory to learn effectively (Dunlosky et al. 2013; Soderstrom and Bjork 2015). Students frequently employ visual strategies (like conceptual maps, tables) and summarization strategies (like formulating concise statements) to organize information into efficiently processable sequences (Moola et al. 2020; Weinstein, Sumeracki, and Caviglioli 2019). Studies have shown that using visual enhances retention, as these summarization and synthesis strategies are positively associated with self-regulated learning (Dunlosky et al. 2013; Jaeger and Fiorella 2023; Nesbit and Adesope 2006).

Deep Information Processing Strategies: In line with cognitive theory, both associating new information with existing structures and restructuring existing information are crucial for successful knowledge acquisition (Soderstrom and Bjork 2015). Learning strategies that activate these types of processes include relating new material to existing knowledge, applying learned concepts to real-life situations, and considering alternative solutions to real-world problems. Though cognitively demanding, these activities significantly enhance learning (Panadero, Jonsson, and Strijbos 2016; Panadero et al. 2021).

Social Regulation Strategies in Learning: Learning does not occur in isolation but rather within social contexts that influence regulation. Processes such as co-regulation and socially distributed regulation are common in classrooms, facilitated by teachers and peers (Allal 2020; Chan, Wan, and Ko 2019; Wu, Goh, and Mai 2023). Furthermore, group work has become a staple in classrooms, requiring students to collaborate effectively in ever-changing and complex scenarios. However, it's important to note that social interaction does not always yield positive learning outcomes, as evidenced by the work of Ndiku Makewa et al. (2014).

1.3. The current study: aims, research objectives and hypotheses

This paper is centered on fulfilling two primary research objectives (ROs):

RO1: The first objective is to examine the internal validity of the Deep Learning Strategies Questionnaire, as initially created by Panadero et al. (2021), specifically within the context of Romanian student populations.

RO2: The second objective involves investigating how deep learning strategies interact with three critical elements that influence learning in higher education. These elements are self-efficacy, subjective well-being, and academic performance. We have formulated specific hypotheses regarding these relationships (see **Figure 1**):

H1: Deep learning self-regulated learning strategies influence the perception of self-efficacy and, together, influences the subjective well-being of students.

H2: Deep learning self-regulated learning strategies influence the perception of self-efficacy and, together, influences the academic performance of students.

H3: Subjective well-being mediates the effect of self-regulation learning strategies on academic performance.

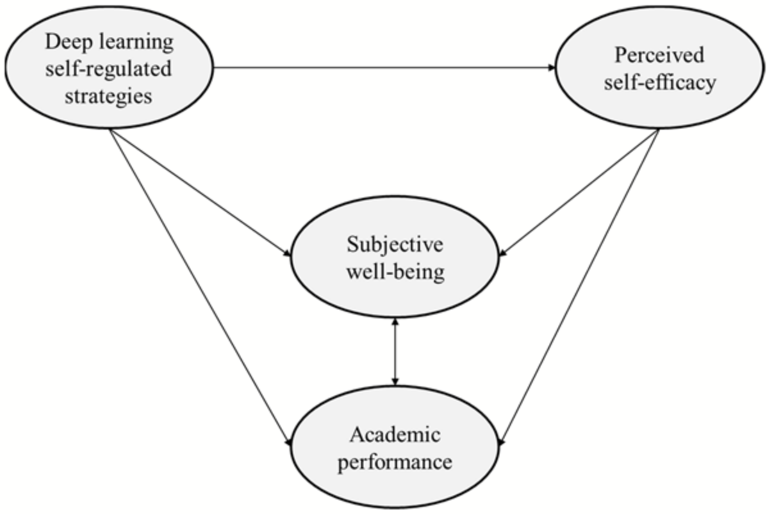

Figure 1. Theoretical model

Note: Developed by the authors

2. Methods

2.1. Study design and Participants

This quantitative study was conducted using a correlational-cross-sectional design. The study incorporated a sample of 130 university students selected based on availability criteria from four Romanian higher education institutions.

The composition of the study's participants primarily consisted of undergraduate students, accounting for 82%, while Master's students comprised the remaining 18%. Among the undergraduates, the breakdown was as follows: freshmen (44.6%), sophomores (22.3%), juniors (20.8%), and seniors (12.3%). The average age of the participants was 21.2 years

($M = 21.22, SD = 2.79$). In terms of gender distribution, females constituted the majority, representing 57% of the sample, which translates to 74 female participants.

2.2. Instruments

In order to encompass all the dimensions underlying the theoretical model, a multidimensional questionnaire was designed. It comprised: (1) sociodemographic items (items 1-6); (2) items dedicated to learning strategies (items 7-36); (3) items related to perceived self-efficacy (4 items); (4) the short version of the Oxford questionnaire for subjective happiness (8 items); academic performance measured as the annual average grade and semestrial average grade (2 items).

The Deep Learning Strategies Questionnaire, initially validated by Panadero et al. (2021), is structured in its final format to include 30 items. Respondents are prompted to answer using a 5-point Likert scale, spanning from 'Totally Disagree' to 'Totally Agree.' The questionnaire is designed to represent various types of strategies aimed at deep learning. It encompasses four distinct sections including S1 - Basic learning self-regulation strategies (8 items), S2- Visual elaboration and summarizing strategies (8 items), S3 - Deep information processing strategies (8 items), , and S4 - Social learning self-regulation strategies (6 items) (Panadero et al. 2021, 14). Cronbach's alpha coeficient ranged from 0.717 to 0.823 (see **Table 2**), indicating a good to very good internal consistency of each dimension included in the model.

Table 2. Deep learning strategies questionnaire. Values of Cronbach's alpha coefficients

Dimensions	Standardized Cronbach's alpha	Number of items
S1 – learning self-regulation strategies	0,752	8
S2 – visual elaboration and summarizing strategies	0,823	8
S3 – deep information processing strategies	0,821	8
S4 - social elaboration study strategies	0,717	6

Student Well-Being Scale. The measurement of student subjective well-being was conducted using eight items, constituting the abbreviated version of the Oxford Happiness Questionnaire (OHQ, $\alpha = 0.757$) (Hills and Argyle 2002). Each item among the eight was assessed on a 5-point Likert scale: 1 representing 'to a very little extent,' and progressing to 5, which stands for 'to a very large extent'

Self-efficacy for learning and performance scale. In order to measure the self-efficacy perception, the authors have formulated contextual five items to present the potentially anxiogenic situations, building upon the approach proposed by Bermejo-Toro et al. (Bermejo-Toro, Prieto-Ursúa, and Hernández 2016; Manasia, Pârvan, and Macovei 2020). Each item was associated with an item, formulating in a projective manner the capability to provide an adequate answer to the situation described. Each of the five items presenting potentially stressful situations was followed by the question: "When you find yourself in a situation similar to the one above, to what extent do you believe you can manage it?" ($\alpha = 0.720$) (Bermejo-Toro, Prieto-Ursúa, and Hernández 2016). The answer to the question was recorded on a 5-point Likert scale (1 = to a very little extent, 2 = to a little extent, 3= to a moderate extent, 4 = to a large extent, 5 = to a very large extent).

Academic performance was evaluated based on the average grade reported at the conclusion of the academic semester.

2.3. Procedure

In an effort to garner participants for the research, formal outreach was made to multiple higher educational institutions across the country. These institutions were requested to circulate the study invitation among their student body. This invitation encompassed a link for interested students to register their email addresses to obtain the questionnaire. To ensure the legitimacy of the email database, which accumulated to around 520 entries, the online platform email-checker.net was utilized. Following the validation, an invitation to partake in the survey was disseminated via e-mail, attaining a response rate of approximately 25%. Emphasizing the voluntary and anonymous nature of this study, participants were assured that no personal information gathered would be used for identification, and their email addresses would remain unassociated with the data collected. Non-consenting individuals were provided with the option to refrain from completing the survey. At the commencement of the survey and within the initial email containing the questionnaire link, subjects were informed about the research's nature, purpose, and estimated duration. The researchers' names and affiliations were openly disclosed for additional transparency. A statement within the questionnaire further affirmed the principle of voluntary participation, signifying that proceeding with the questionnaire symbolized their consensual involvement in the study. Participants were guaranteed exclusive use of their responses for research objectives, reinforcing the commitment to confidentiality and ethical research conduct.

2.4. Data Analysis

Analysis of the accumulated data was executed with JASP version 0.18.1. This analysis incorporated both descriptive and inferential statistics, along with structural equation modeling, ensuring a robust and comprehensive examination of the hypotheses. In this study, Principal Axis Factoring was utilized in an exploratory manner to identify the primary factors delineated by the variables and to condense the data to a more manageable set of variables. This factor analysis was independently conducted for each dimension encompassed in the theoretical model, namely subjective well-being, the four types of learning strategies, and self-efficacy. This procedure allowed for a reduction in variable number and a test of unidimensionality for each latent variable. Notwithstanding, given the separate and exploratory nature of these analyses, subsequent validation was deemed necessary. To validate the findings from the factor analysis and test the hypotheses, structural equation modeling was employed. In order to test the internal validity of the deep learning self-regulated strategies model, several models were tested. First, as a base, we used a structure in which the five dimensions of deep learning self-regulated strategies correlated with each other (Model SEM 1). Second, Model SEM 2 examined if the five primary factors related to the strategies served as indicators for a comprehensive construct termed Deep Learning Strategies. Thirdly, a mediation model was tested, according to which self-efficacy mediated the effect of deep self-regulated strategies on student subjective well-being and performance. Aligning with the guidelines proposed by Hooper et al. (2008), the computed normed/relative chi-square (X^2/df) was ensured to fall within the 2 to 5 range. Additional fit indices, such as RMSEA, GFI, AGFI, RFI, and TLI, were also calculated and scrutinized. Adhering to the recommendations by MacCallum et al. (1996), an RMSEA value within 0.05 to 0.08 was deemed indicative of a fair model fit, with more contemporary scholarly consensus advocating for values below 0.07 for an appropriate model fit. Concerning the GFI, AGFI, CFI, and TLI indices, values approaching the 0.95 threshold were sought as per Hooper et al. (2008), while values within the 0.85 to 0.95 range were considered to demonstrate a satisfactory model fit to the empirical data as per MacCallum et al. (1996). This study followed these prescribed criteria and acceptable thresholds to ensure the robustness and validity of the conducted analyses.

3. Results

The present paper aimed at validating a model of deep learning self-regulation strategies and test their relation with student well-being, perceived self-efficacy, and academic performance. Thus, the model assumes that perceived self-efficacy mediates the effect of self-regulation learning strategies and, together they influence student subjective well-being, this mediating the influence of the first two factors on academic performance. Complementarily, the direct influence of learning regulation strategies on academic performance will be tested.

3.1. Descriptives

Table 3 presents descriptive statistics (mean – M, standard deviation – SD, minimum – Min, and maximum – Max values) for the observed variables included in the statistical models.

The variables (statements) that manifested the highest mean values pertained to participants' inclination towards a comprehensive understanding and analysis of tasks, alongside a rigorous post-task completion review. Elevated mean scores were registered for variables epitomizing diverse facets of task comprehension and execution strategies. The variable S1_28, representing the practice of thoroughly reading and understanding instructions for assignments and exams, reported the uppermost mean value (M = 4.62, SD = 0.59).

Following closely were the variables S1_1 and S1_4, signifying in-depth task analysis (M = 4.38, SD = 0.74) and commitment to task visualization and follow-through (M = 4.32, SD = 0.86), respectively. Furthermore, the variable S1_20, indicating a post-task completion review to ascertain correctness (M = 4.25, SD = 0.99), also documented a high score, underscoring the significance participants attribute to self-evaluation and task reassessment.

Table 3. Descriptive statistics for the variables included in the statistical models (N=130)

Variables	Min	Max	M	SD	Skewness	Kurtosis
S1_1	2	5	4.38	.739	-.968	.330
S2_2	1	5	3.02	1.403	-.062	-1.330
S3_3	1	5	3.54	1.038	-.647	-.036
S1_4	1	5	4.32	.863	-1.543	2.805
S2_5_rev	1	5	4.30	1.001	-1.529	2.005
S3_6	1	5	3.85	1.053	-.902	.551
S4_7	1	5	3.44	1.329	-.489	-.947
S1_8	1	5	4.09	.944	-.861	.124
S2_9_rev	1	5	2.80	1.332	.174	-1.138
S3_10	1	5	4.01	.992	-1.128	1.347
S4_11	1	5	3.01	1.171	-.045	-.805
S1_12	1	5	3.84	1.055	-.958	.599
S2_13	1	5	3.99	1.165	-1.061	.320
S3_14	1	5	4.02	.906	-.919	.867
S4_15	1	5	3.27	1.316	-.366	-1.067
S1_16	1	5	3.83	1.005	-.816	.403
S2_17	1	5	3.81	1.201	-.956	.108
S3_18	1	5	3.94	.896	-.930	1.278

Variables	Min	Max	M	SD	Skewness	Kurtosis
S4_19	1	5	3.67	1.248	-.734	-.422
S1_20	1	5	4.25	.989	-1.442	1.704
S2_21_rev	1	5	3.11	1.163	-.153	-.688
S3_22	1	5	3.81	1.027	-.650	-.144
S4_23	1	5	3.30	1.211	-.252	-.952
S1_24	1	5	3.63	1.156	-.524	-.489
S2_25_rev	1	5	3.23	1.417	-.187	-1.312
S3_26	1	5	3.88	.881	-.655	.561
S4_27	1	5	3.44	1.264	-.433	-.845
S1_28	2	5	4.62	.589	-1.500	2.424
S2_29	1	5	3.19	1.333	-.127	-1.183
S3_30	1	5	4.11	.917	-1.135	1.273
AUTOEF1	2	5	3.68	.891	.019	-.848
AUTOEF2	1	5	3.27	.958	-.137	-.323
AUTOEF3	1	5	3.43	1.007	-.400	-.040
AUTOEF4	1	5	2.64	1.030	-.002	-.673
OHQ_1_rev	1	6	3.89	1.506	-.244	-.977
OHQ_2	1	6	3.86	1.435	-.315	-.727
OHQ_3	1	6	3.99	1.476	-.282	-.860
OHQ_4_rev	1	6	3.83	1.626	-.241	-1.085
OHQ_5	1	6	4.88	1.250	-1.224	1.308
OHQ_6	1	6	3.20	1.761	.124	-1.316
OHQ_7	1	6	2.88	1.332	.196	-.677
OHQ_8_rev	1	6	3.61	1.697	-.055	-1.294
PERF	5	10	8.55	0.87	-.704	1.428

Source: Developed by the authors based on the collected data

3.2. Results of the Factor Analyses

Deep Learning Strategies

At first, the factorability of the 30 items in the Deep learning strategies questionnaire was tested. Confirmatory factor analysis was performed to test the solution with four factors proposed by Panadero et al (Panadero et al. 2021). The Kaiser–Mayer–Olkin measure of sampling adequacy indicated that factor analysis is suitable for these data, with an overall MSA of $KMO = 0.82$. Most individual variables also have an MSA above 0.8, indicating good sampling adequacy. The Bartlett's test was statistically significant: $X^2(406, N = 130) = 1515.57, p < 0.001$, confirming that the data is suitable for factor analysis. The fit indices computed suggested that the model does not adequately fit the data. Most of the indices are below the commonly accepted thresholds for a good fit. The chi-square test for model adequacy was statistically significant, suggesting that the model does not fit the data well: $X^2(371, N = 130) = 652.371, p < 0.001$. Additional fit measures were computed. The adjusted chi-square value $X^2/2 = 326.165$ both indicates a poor fit to the observed data. Additionally, the low values of Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), 0.78 and 0.75 respectively, further reinforce this conclusion. These cumulative results signaled the imperative need for revising the current model or considering alternative models to enhance the fit to the data.

Therefore, we applied exploratory factor analysis (EFA), based on principal axis factoring (PAF) Similarly, the data were adequated for factor analysis: $KMO = 0.81$ and the Bartlett's test was statistically significant: X^2(348, N=130) = 524.8, p<0.001). The uniqueness values of the thirty variables ranged from 0.2 (S4_27) to 0.9 (S1_28). Several items (e.g., S2_5_neg, S2_9_neg, S1_28) have high uniqueness values, exceeding 0.70, suggesting that these items were not well-represented by the identified factors and might not fit well in the factor structure. In assessing the multivariate normality of the dataset, Mardia's tests for skewness and kurtosis were conducted. The test for multivariate skewness yielded a value of 298.12 with a chi-square statistic of $X^2 = 6310.39, (df = 4960, p < 0.001)$, indicating significant multivariate skewness in the dataset. The small sample skewness reported similar findings with a value of 298.12 and a chi-square statistic of $X^2 = 6469.15, (df = 4960, p < 0.001)$. Furthermore, the test for multivariate kurtosis exhibited a value of 1013.50 with a Z-value of 6.88 (p<0.001), denoting significant kurtosis. These results collectively suggest a violation of the assumption of multivariate normality in the dataset.

EFA was re-run after eliminating the ten items with uniqueness values over 0.7 from the analysis. A solution with 4 factors was revealed, indicating an improved and more reliable factor structure. **Table 4** presents the goodness of fit indices for the re-specified model of deep learning strategies.

Table 4. Goodness of fit indices of the deep learning strategies model, N = 130.

Model	X^2	df	p	X^2/df	$RMSEA$	TLI	CFI
Re-specified model of Deep learning strategies	115.96	100	0.13	1.15	0.03	0.96	0.98

Note: Developed by the authors

The factor structure presented in **Table 5** emerges as more robust and insightful for interpreting and assessing deep learning strategies. Each of the five factors possesses eigenvalues exceeding 1, collectively accounting for 53% of the variance in the deep learning strategies employed by students. This enhanced model promises improved reliability and validity in exploring and understanding the depth of learning strategies in educational contexts.

Table 5. Summary factor analysis and eigenvalues

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness	Eigenvalues
S2_25_neg	0.8					0.39	5.84
S2_29	0.7					0.42	
S2_2	0.69					0.47	
S2_21_neg	0.67					0.51	
S2_17	0.66					0.4	
S3_10		0.84				0.26	2.29
S3_18		0.71				0.47	
S3_6		0.53				0.53	
S4_11		0.46				0.6	
S3_14		0.45				0.54	
S4_27			0.92			0.16	2.07
S4_7			0.76			0.43	
S4_15			0.58			0.6	
S1_4				0.82		0.35	1.32
S1_1				0.46		0.69	
S1_12				0.42		0.58	
S1_20				0.40		0.69	
S3_22					0.97	0	1.12
S3_26					0.5	0.63	
S3_3					0.5	0.66	

Note. Applied rotation method is oblimin.

A parallel analysis was conducted using characteristics identical to those of the dataset. This analysis indicated that retention should be limited to only three factors, where the eigenvalues exceeded those of factors generated randomly, as suggested by Yaguarema et al. (2022).

Perceived self-efficacy

Similar to the way in which we proceeded for testing the deep learning self-regulation strategies model, EFA with PAF analyses were also conducted for the items associated with the self-efficacy dimension. The collected data are suitable for factorial analysis: $KMO = 0.81$, and Bartlett's test is statistically significant ($BST = 218.77, df = 6, p < 0.001$). The inter-item correlations are of low to medium intensity, statistically significant. The uniqueness scores have values between 0.30 and 0.58. A varimax rotation was used to simplify the factor loadings. Overall, the fit indices in **Table 6** suggest that the model fits the data very well.

Table 6. Goodness of fit indices. Self-efficacy, N = 130.

Model	X^2	df	**p**	X^2/df	$RMSEA$	TLI	**CFI**
Self-efficacy	3.20	5	0.67	0.64	0.00	0.98	1.00

Note: Developed by the authors

A single factor was extracted. Thus, all four items, viewed as observed variables, load on a single factor, whose eigenvalue is greater than 1 and explains approximately 59% of the variation of the latent variable self-efficacy (

Table 7). The resulting factorial score (calculated by the regression method) was saved and was used for additional analyses to substantiate the factorial model of students' academic performance.

Table 7. Summary factor analysis and eigenvalues

Factor	**Item**	**Factor loading**	**Uniqueness**	**%Variance Explained Cumulative**	**Eigenvalues**
Factor : Perceived self-efficacy	AUTOEF2	0.84	0.3	0.59	2.76
	AUTOEF1	0.82	0.33		
	AUTOEF3	0.76	0.42		
	AUTOEF4	0.65	0.58		

Note: Applied rotation method is varimax.

Subjective well-being

The factor structure of Subjective Well-Being has been valuated using EFA with PAF as the extraction method. The data are relatively suitable for factor analysis, as indicated by a KMO measure of sampling adequacy of 0.77 and a statistically significant Bartlett's Test of Sphericity ($BST = 295.17, df = 28, p < 0.001$). Despite the range of uniqueness scores from 0.21 to 0.95, all items within the model have been retained due to their theoretical relevance to the construct of subjective well-being. This decision underscores the pivotal role of theoretical grounding in model building, ensuring that each item's conceptual contribution is carefully weighed alongside statistical metrics. The use of Varimax rotation further simplifies the factor loadings, contributing to an overall good model fit as suggested by the fit indices in **Table 8**.

However, it is noteworthy that the RMSEA of 0.10 is slightly higher than the ideal threshold, pointing to a potential avenue for enhancing the model fit. Despite the low p-value (<0.001) indicating a discrepancy between the model and the data, the $X^2/df = 2.27$,

$TLI = 0.87$, and $CFI = 0.90$ are within an acceptable range, highlighting a reasonable fit of the model.

Table 8. Goodness of fit indices. Subjective well-being, N = 130.

Model	X^2	df	p	X^2/df	$RMSEA$	TLI	CFI
Subjective well-being	45.45	20	<0.001	2.27	0.10	0.87	0.90

Note: Developed by the authors

Table 9 displays the summary factor analysis and eigenvalues. A single factor has been extracted, with an eigenvalue greater than one, explaining approximately 34% of the variance of the latent variable, subjective well-being. The ensuing factorial score, computed via the regression method, is earmarked for further analyses to substantiate the factorial model of students' academic performance.

Table 9. Summary factor analysis and eigenvalues

Factor	Item	Factor loading	Uniqueness	%Variance Explained Cumulative	Eigenvalues
Factor : Subjective well-being	OHQ_2	0.89	0.21	0.34	3.21
	OHQ_3	0.78	0.39		
	OHQ_4_rev	0.67	0.55		
	OHQ_1_rev	0.6	0.64		
	OHQ_7	0.42	0.82		
	OHQ_5		0.95		
	OHQ_6		0.9		
	OHQ_8_rev		0.84		

Note: Applied rotation method is varimax.

3.3. Results of the SEM analyses

Model SEM 1 – Intercorrelated factors of the deep learning strategies model

We present the first model in Figure 3. The data were run through JASP with Diagonally Weighted Least Squares estimation, and the results (**Table 10**) indicate an acceptable fit. The skewness and kurtosis statistics indicated a violation of the univariate normality. Thus, the data were bootstrapped with 1000 draws at the 95% bias-corrected confidence level.

The χ^2 value is 218.76 with 179 degrees of freedom, and the p-value is 0.02. Typically, a non-significant p-value is desired, indicating a good fit of the model. TLI and CFI indices are close to 1, indicating an excellent fit to the data. The RMSEA value is 0.04, with a 90% CI between 0.02 and 0.06 and a p-value of 0.75. The GFI is 0.97, also indicating a good fit. The residual variance estimates are quite varied, ranging from as low as 0.09 to as high as 0.70. Most of the estimates are around the 0.4 to 0.6 range, which is a moderate level of residual variance.

Table 10. Goodness of fit indices Model 1, N = 130

Model	X^2	df	p	X^2/df	$RMSEA$	TLI	CFI	GFI
Model SEM 1 – Intercorrelated factors of the deep learning strategies model	218.76	179	0.02	1.22	0.04	0.99	0.99	0.97

Note: Developed by the authors

All the covariances between the factors were statistically significant. The p-values are less than 0.001 for most factor pairs, strongly affirming the statistical significance of the covariances. The exception is the covariance between Factor 4 and Factor 5, though it is still significant with a p-value of $p = 1.93 \ * 10^{-3}$. The covariances between certain pairs of factors (for example, Factor 1 and Factor 5) are comparatively higher, signaling a stronger relationship. Conversely, pairs like Factor 4 and Factor 5 exhibit a weaker relationship.

Table 11. Model SEM 1. Factor covariances

					95% Confidence Interval		Standardized		
Variables	**Estimate**	**Std. Error**	**z-value**	**p**	**Lower**	**Upper**	**All**	**LV**	**Endo**
Factor1 - Factor2	0.29	0.02	11.96	< .001	0.17	0.39	0.50	0.50	0.50
Factor1 - Factor3	0.28	0.03	10.38	< .001	0.12	0.41	0.60	0.60	0.60
Factor1 - Factor4	0.16	0.03	5.61	< .001	-0.03	0.32	0.23	0.23	0.23
Factor1 - Factor5	0.41	0.03	12.39	< .001	0.24	0.52	0.65	0.65	0.65
Factor2 - Factor3	0.27	0.03	9.54	< .001	0.15	0.38	0.54	0.54	0.54
Factor2 - Factor4	0.20	0.03	6.14	< .001	0.01	0.35	0.27	0.27	0.27
Factor2 - Factor5	0.26	0.03	7.81	< .001	0.07	0.38	0.38	0.38	0.38
Factor3 - Factor4	0.19	0.03	5.41	< .001	-0.02	0.33	0.31	0.31	0.31
Factor3 - Factor5	0.26	0.04	7.26	< .001	0.07	0.39	0.47	0.47	0.47
Factor4 - Factor5	0.14	0.04	3.10	1.93×10^{-3}	-0.08	0.34	0.16	0.16	0.16

Note: Developed by the authors

Model SEM 2 – Hierarchical model of the deep learning strategies

The objective of this analysis was to examine if the five primary factors related to the strategies serve as indicators for a comprehensive construct termed Deep Learning Strategies. As depicted in **Table 12**, the goodness of fit for this model is comparable to that of Model 1. Even though the Chi-square was significant, other fit indices such as the ratio of X^2/df, the RMSEA, TLI, and CFI were comfortably within the acceptable thresholds, permitting the acceptance of this model.

Table 12. Goodness of fit indices Model 2 (N=130)

Model	X^2	df	**p**	X^2/df	$RMSEA$	TLI	**CFI**	**GFI**
Model SEM 2 – Hierarchical model of the deep learning strategies	212.74	165	7.22×10^{-3}	1.28	0.05	0.99	0.99	0.97

Note: Developed by the authors

All relationships between the latent variables (

Table *13*) and their indicators are statistically significant $p < 0.001$. The estimates of these relationships vary, with values ranging from 0.53 to 1.13. The 95% confidence intervals for each relationship further corroborate these findings, with none encompassing zero, reinforcing the reliability and consistency of the path coefficients. The standardized estimates, ranging from 0.33 to 0.97, provide additional affirmation of the varying strengths in relationships between latent variables and indicators.

Table 13. *Second-order factor loadings*

Factor	Indicator	Estimate	Std. Error	z-value	p	95% Confidence Interval Lower	Upper	Std. Est. (all)
Deep learning strategies	Factor 1	0.64	0.12	5.41	< .001	0.41	0.87	0.54
	Factor 2	1.98	0.55	3.59	< .001	0.90	3.06	0.89
	Factor 3	0.32	0.11	2.95	3.15×10-3	0.11	0.53	0.30
	Factor 4	1.53	0.34	4.53	< .001	0.87	2.19	0.84
	Factor 5	1.56	0.39	3.98	< .001	0.79	2.33	0.84

Factor loadings

Factor	Indicator	Estimate	Std. Error	z-value	p	95% Confidence Interval Lower	Upper	Std. Est. (all)
Factor 1	S2_25_neg	0.67	0.05	14.04	< .001	0.58	0.77	0.80
	S2_29	0.67	0.05	13.24	< .001	0.57	0.77	0.80
	S2_2	0.65	0.05	12.05	< .001	0.54	0.75	0.77
	S2_21_neg	0.58	0.05	10.89	< .001	0.48	0.68	0.69
	S2_17	0.67	0.05	13.61	< .001	0.57	0.77	0.80
Factor 2	S3_10	0.34	0.08	4.50	< .001	0.19	0.49	0.76
	S3_18	0.33	0.07	4.43	< .001	0.18	0.48	0.73
	S3_6	0.33	0.08	4.32	< .001	0.18	0.49	0.74
	S4_11	0.25	0.06	3.99	< .001	0.13	0.38	0.56
	S3_14	0.34	0.08	4.52	< .001	0.19	0.49	0.76
Factor 3	S4_27	0.91	0.07	13.62	< .001	0.78	1.04	0.95
	S4_7	0.71	0.05	13.69	< .001	0.61	0.81	0.74
	S4_15	0.62	0.06	11.20	< .001	0.52	0.73	0.65
Factor 4	S1_4	0.29	0.06	4.77	< .001	0.17	0.41	0.53
	S1_1	0.35	0.08	4.47	< .001	0.20	0.50	0.64
	S1_12	0.40	0.07	5.69	< .001	0.26	0.53	0.73
	S1_20	0.34	0.07	4.94	< .001	0.21	0.48	0.62
Factor 5	S3_22	0.42	0.08	5.39	< .001	0.27	0.57	0.78
	S3_26	0.37	0.06	6.29	< .001	0.26	0.49	0.70
	S3_3	0.35	0.08	4.32	< .001	0.19	0.51	0.65

Note: Developed by the authors

Reliability

In addition to evaluating fit indices, an analytical diagnosis of the models was performed. The summary of Cronbach's alpha, McDonald ω, and Average Variance Extracted (AVE) is presented in Table 13. Each scale reflects a range from acceptable to high internal consistency. Despite some scales having AVEs marginally below the 0.5 threshold, hinting at potential concerns regarding their construct validity, the majority display robust metrics. This underscores their reliability and validity in assessing diverse learning strategies.

Table 14. Reliability of the Deep Learning Strategies Questionnaire

Scale	Cronbach's alpha	McDonald ω	AVE
Deep learning strategies questionnaire (20 items)	0.86	0.84	0.52
Visual elaboration and summarizing strategies	0.85	0.84	0.52
Integrative Reflective Learning	0.79	0.80	0.51

Strategies			
Social learning self-regulation strategies	0.80	0.80	0.63
Basic learning self-regulation strategies	0.68	0.68	0.40
Practical Application and Critical Analysis Strategies	0.73	0.70	0.50

Note: Developed by the authors

Mediation analysis

In the current study, a mediation analysis was conducted to examine the indirect effects of deep learning self-regulated strategies (DEEP) on students' average grades (AVEG) and subjective well-being (WB), through perceived self-efficacy.

presents the path diagram.

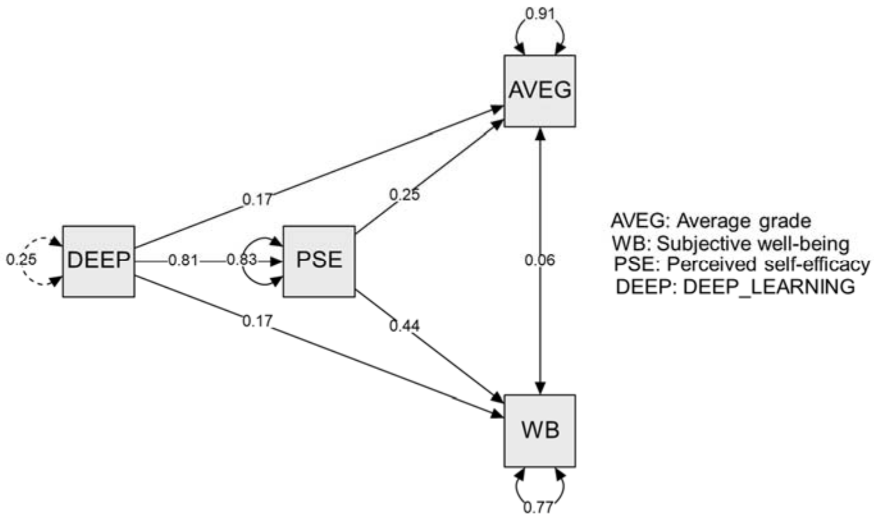

Figure 2. Path diagram

Note: Developed by the authors in JASP 0.18.1

The path diagram provided delineates the relationships among four key constructs: DEEP (Deep Learning), PSE (Perceived Self-Efficacy), AVEG (Average Grade), and WB (Subjective Well-Being). The model encapsulates both direct and indirect pathways through which these constructs are hypothesized to interact.

In the proposed model, deep learning is posited as a foundational construct that exerts a significant direct effect on Perceived Self-Efficacy (PSE), indicated by a substantial path coefficient of 0.83. This suggests a strong positive relationship where deeper engagement in learning is associated with increased self-efficacy. Additionally, PSE shows positive direct effects on both Average Grade (AVEG) and Subjective Well-Being (WB), with path coefficients of 0.25 and 0.44, respectively. These paths indicate that students with higher self-efficacy are likely to achieve better grades and report higher well-being.

Moreover, the model highlights the mediating role of PSE between DEEP Learning and the outcomes of AVEG and WB, as reflected by the indirect effects with path coefficients of 0.17 for both outcomes. This mediation suggests that the influence of deep learning on grades and well-being is partially channeled through self-efficacy beliefs.

Notably, AVEG is also shown to have a strong direct effect on subjective well-being with a path coefficient of 0.91. This implies that academic performance is a critical determinant of students' subjective well-being, potentially overshadowing other factors.
The variance explained in the model for DEEP Learning is relatively low (0.25), indicating that other factors not included in the model might contribute to the development of deep learning approaches. In contrast, the model accounts for a considerable proportion of the variance in Subjective Well-Being (0.77), suggesting that the included constructs are significant contributors to students' well-being.

4. Discussion and conclusions

This study aimed to evaluate the internal validity of the Deep Learning Self-Regulation Strategies Questionnaire, originally developed by Panadero et al. (2021). Additionally, it sought to examine the relationship between deep learning strategies and student academic performance, perceived self-efficacy, and subjective well-being.

Initially, the factorability of the 30 items in the Deep Learning Strategies Questionnaire was assessed and deemed satisfactory. Consequently, Confirmatory Factor Analysis (CFA) was employed to evaluate the model structure initially proposed by Panadero et al. (2021). However, the original model did not demonstrate acceptable fit, necessitating a re-specification. Subsequently, a five-factor solution emerged, identifying the following learning strategies: *Visual Elaboration and Summarizing Strategies, Integrative Reflective Learning Strategies, Social Learning Self-Regulation Strategies, Basic Learning Self-Regulation Strategies, and Practical Application and Critical Analysis Strategies*. Therefore, the model proposed in this study suggests a revised factor structure with five factors, in contrast to the four-factor structure originally reported by Panadero et al. (2021). It is important to note that the sequence in which the factors are presented does not represent the progressive stages of the self-regulated learning process. Rather, this order corresponds to the manner in which the factors were extracted during the analysis. For the sake of maintaining consistency in reporting our findings, we have chosen to retain this original order.

The first factor in our model, termed *Visual Elaboration and Summarizing Strategies*, encompasses strategies utilized for visually processing learning materials. This factor aligns with findings from Panadero et al. (2021) and Yaguarema et al. (2022), corroborating its relevance in educational research. Substantial empirical support underscores the effectiveness of these strategies, as highlighted in studies by Jaeger & Fiorella (2023) and Weinstein et al. (2019). The specific items that loaded onto this factor (namely, items 2, 17, 21, 25, and 29) are directly linked to both visual and verbal elaborations. These include activities such as creating graphs, diagrams, concept maps, charts, tables, and summaries, all of which are integral to this factor.

The second factor we identified referred to *integrative reflective learning strategies*. Items such as relating study material to what is already known, and connecting class content to personal ideas (i.e., items 10, 6, 18, 14), demonstrate an integrative approach to learning. This suggests a deep processing of information, where new knowledge is integrated with existing cognitive structures. Reflective and integrative learning is a progressive process influenced by various factors and student experiences, both within and beyond the classroom setting, throughout their university education (Awang-Hashim et al. 2022; Bransen et al. 2022; Youngerman 2018). Research in the field of deep learning indicates that educators and institutions emphasizing the cultivation of reflective and integrative learning skills tend to offer students opportunities to explore complex topics extensively. This approach includes encouraging students to engage in profound reflection, scrutinize and assess their own viewpoints, juxtapose them with differing perspectives, and ultimately synthesize disparate information segments into a cohesive and meaningful interpretation (Awang-Hashim et al. 2022; Barton and Ryan 2014). Barber (2012) defines reflective and integrative learning as "the capacity to coherently connect, apply, and synthesize information from various contexts and viewpoints, utilizing these newfound insights across multiple situations" (p. 593). This factor, primarily associated with the concept of integrative learning, also incorporates an element related to co-regulatory strategies (Bransen et al. 2022), as evidenced by item 11.

The third factor, *Social Learning Self-Regulation Strategies*, captures the essence of active engagement with peers in the learning process, both through discussion of study topics and seeking feedback on task performance, as suggested by Panadero et al. (2021), and Yagurema et al. (2022). Items 7, 15, and 27 pertain to interactions with students in a learning context. These items potentially represent the social dimensions of self-regulated learning, encompassing scenarios where students seek support (external regulation), exercise self-regulation, influence the regulation of others, and engage in group-based regulation during tasks (Bransen et al. 2022; McNamara 2011; Mega, Ronconi, and De Beni 2014; Panadero 2017; Panadero, Jonsson, and Strijbos 2016).

The fourth factor, Basic Learning Self-Regulation Strategies, identifies a series of fundamental steps that learners undertake to effectively manage and assess their learning process (Zimmerman 2000), involving metacognitive planning, monitoring, and evaluation (Jaeger and Fiorella 2023; Winne 2022). Firstly, it involves an analysis of the task at hand. This is where learners delve deeply into the requirements and objectives of the task, ensuring they have a clear understanding of what is expected of them. Subsequently, learners engage in a process of visualization and implementation. Moreover, the factor includes the utilization of self-assessment tools provided by educators. This aspect underscores the value of reflection and self-evaluation in the learning process (Kostons, van Gog, and Paas 2012; Panadero, Brown, and Strijbos 2016; Panadero, Jonsson, and Strijbos 2016). Finally, the factor is rounded out with a post-task review. This is where learners reflect on their completed work, analyzing it critically to ascertain if it meets the set standards and objectives. While this factor was included in the initial model (Panadero et al. 2021; Yaguarema, Zambrano R., and Salavarría 2022), subsequent reliability analysis revealed suboptimal indices $Cronbach's\ \alpha = 0.68;\ \omega = 0.68: AVE = 0.40$.

Finally, the fifth factor, *Practical Application and Critical Analysis Strategies,* encompassed items related to deep information processing strategies (i.e., 3, 22, 26), aligned with the concrete processing strategies in the learning patterns model (Gijbels et al. 2013; Martínez-Fernández and Vermunt 2015; Shum et al. 2023; Vanthournout et al. 2013; Vermunt and Donche 2017; Vermunt and Vermetten 2004).

The findings of our study indicate a requirement for a more refined approach to deep information processing learning strategies. This approach should specifically encompass the nuances of integrative learning and concrete processing strategies. Furthermore, the study's results are derived from a condensed version of the Deep Learning Strategies Questionnaire (Panadero et al. 2021). This reduction involved the exclusion of 10 items from the analysis, attributed to their high uniqueness values.

The second research objective of the paper was to offer insights into the interplay between deep learning strategies, perceived self-efficacy, average grades, and subjective well-being among students. The findings reveal that deep learning strategies (DEEP) are a robust predictor of perceived self-efficacy (PSE), which in turn significantly influences average grades (AVEG) and subjective well-being (WB).

The substantial direct effect of DEEP on PSE (path coefficient = 0.83) aligns with previous educational research suggesting that deep learning approaches are closely linked to students' confidence in their learning abilities (Ciolan and Manasia 2017; Panadero et al. 2021). This relationship underscores the importance of educational practices that promote in-depth understanding and critical thinking, as these strategies appear to bolster students' self-efficacy.

Further, the model elucidates the mediating role of PSE between DEEP and the students' academic outcomes (AVEG) and well-being (WB), with indirect effects quantified by path coefficients of 0.17 for both variables. This mediation is in consonance with Bandura's self-efficacy theory (Bandura 2010; Wang et al. 2023; Zyberaj 2022), which posits that self-efficacy beliefs can significantly mediate the impact of learning strategies on performance outcomes (Öztürk 2022; Wang et al. 2023; Zyberaj 2022). Interestingly, the direct path from AVEG to WB (path coefficient = 0.91) suggests that academic performance is a predominant factor affecting students' subjective well-being. This finding contributes to the burgeoning literature on the link between academic achievement and well-being, emphasizing that successful academic performance may play a more critical role in students' subjective well-being than previously recognized (Checa-Domene et al. 2022; Goetz et al. 2021; Wang et al. 2023). The residual variance in DEEP (0.25) suggests that while deep learning strategies are impactful, other variables not included in the model may also play a role in influencing students' self-efficacy. This opens avenues for future research to explore additional factors, such as classroom environment, teaching practices, or individual student characteristics, that may also contribute to the development of deep learning approaches.

Despite the strengths of the present study, there are limitations to consider. For instance, the relatively low variance explained in DEEP could indicate the need for a more comprehensive measurement that captures the full breadth of deep learning strategies. Additionally, while the model accounts for a significant proportion of variance in subjective well-being (0.77), it does not capture the entirety of the construct, pointing to the complexity of well-being and suggesting that future studies should consider other psychological and contextual factors.

In conclusion, the results of this study have important implications for educators and policymakers. By highlighting the central role of perceived self-efficacy in mediating the relationship between deep learning strategies and both academic and well-being outcomes, it becomes evident that interventions aimed at enhancing self-efficacy could be particularly beneficial. Encouraging deep learning strategies may not only boost academic performance but also contribute to the overall well-being of students.

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