Relationship between cold executive functions and self-regulated learning management in college students

Relación entre las funciones ejecutivas frías y el aprendizaje autorregulado en estudiantes universitarios

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Abstract: The aim of this research was to analyze the relationship between cold executive functions (cEFs), and self-regulated learning management (SRLM) in college students. There is a positive and a statistically significant relationship between cold executive functions (cEFs) and self-regulated learning management (SRLM). This research is a quantitative, cross-sectional, descriptive, and inferential study, with a correlational approach. The sample was non-probabilistic, by convenience sampling, composed of n = 379 college students belonging to pedagogy careers, 64.1% were males, and 35.9% females, aged between 17 and 34 years old (M = 19.82, SD = 2.41). The results show that there is a strong association between cold executive functions and self-regulated learning management since high performance in cEFs would imply a high performance on learning management. On the other hand, it is also observed a predictive value of planning cEF on SRLM, meaning that, an optimal level of planning would imply adequate management of learning processes. The original contribution of this study is to provide evidence to consider supporting plans for college students to improve their skills in the cEFs, due to the negative impact that failure in higher education represents for the student, their families, and university system. Finally, we think it is necessary to continue the research in depth of these variables, and their influence in higher education academic performance.

Keywords: Cold executive functions, Executive functions, Self-regulated learning, Self-regulated learning management, College students.

Resumen: El propósito de esta investigación fue analizar la relación entre las funciones ejecutivas frías (FEf) y la gestión del aprendizaje autorregulado (GAAR) en universitarios, siguiendo la hipótesis de que existe una relación positiva y significativa entre ambas variables. El estudio fue de tipo cuantitativo de corte transversal, con enfoque correlacional, descriptivo e inferencial. La muestra fue de tipo no probabilística incidental, compuesta por n = 379 estudiantes universitarios de carreras de pedagogía, el 64,1% eran hombres y el 35,9% mujeres, de edades entre 17 y 34 años (M = 19,82, SD = 2,41). Los resultados muestran que existe una asociación fuerte entre funciones ejecutivas frías y gestión del aprendizaje autorregulado, dado que un alto rendimiento en FEf implicaría un alto rendimiento en Gestión del Aprendizaje. También se observa un valor predictor de la FEf de planificación sobre la GAAR, es decir, que un buen nivel de planificación implicaría una adecuada gestión de los procesos de aprendizaje. El aporte original de este estudio es presentar evidencias para que en los planes de apoyo a estudiantes universitarios se consideren estrategias que mejoren sus habilidades en las FEf detectadas, dado el impacto negativo que el fracaso en la educación superior tiene para el estudiante, sus familias y el sistema universitario. Finalmente, creemos que es necesario seguir profundizando en estas variables y en su influencia sobre el desempeño académico en la educación superior.

Palabras clave: Funciones ejecutivas, Gestión del aprendizaje autorregulado, Aprendizaje autorregulado, Estudiantes universitarios.

Introduction

Adaptation to university/college life is considered as a complex and critical process for college students due to the series of cognitive strategies and skills (executive functions) that must be implemented to self-regulate their learning, responding adequate to higher education exigences; at the same time, these influence the ability to adapt and academic performance, mainly during the first year courses (freshman year) (Besserra-Lagos *et al.*, 2018; Cazan, 2012; Gallegos *et al.*, 2018; Sáez *et al.*, 2018; Zuñiga-Vilches *et al.*, 2020). In higher education it is key to develop competencies to adapt to the 21st Century, as well as to the different scenarios throughout life (Sáez *et al.*, 2018), between them “Ways of thinking”, mainly, learning to learn, allowing the development of skills to know, manage, and to self-regulate college students own learning process (Binkley *et al.*, 2012).

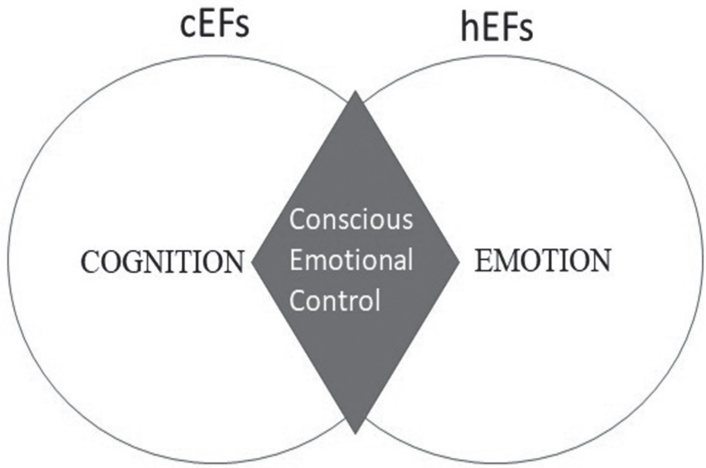
Executive Functions (EFs)

EFs are central higher order cognitive processes necessary to adapt to the environment, since they enable the anticipation of behavior, goal establishment, and conscious control of mental operations and behavior, for effective and efficient resolutions of a problem (Pineda, 2000). Throughout time, there have been different definitions that allow understanding, complimenting, and updating the concept of EFs, since its term was coined by Muriel Lezak in 1982, defining these as the essential mental capacities to carry out an effective, creative and socially accepted behavior, describing four principal components: (1) goal formulation, (2) planning, (3) development, and (4) execution (Bausela Herreras, 2014; Gualpa-Naranjo *et al.*, 2019). On the other hand, these are conceived as a multidimensional construct of skills, higher mental level, affective, and motivational components that are involved in generation, planning, supervision, regulation, execution, and readjustment of appropriate behaviors to achieve complex, goal-oriented objectives, especially those that are considered by a person as novel, and require a creative solution, making possible the functional development of him/herself (Gilbert and Burgess, 2008; Rojas-Barahona, 2017; Tirapu Ustárroz *et al.*, 2017).

EFs are composed of partially interrelated subcomponents, between those, main ones are working memory, inhibitory control, and cognitive flexibility (Bausela Herreras, 2014; Rojas-Barahona, 2017; Santa-Cruz and Rosas, 2017). However, even when there is no a clear consensus about every EF subcomponents, literature suggests that working memory, attentional switching, planning, inhibitory control, cognitive flexibility, updating, monitoring, emotional regulation, organization, and initiative are the central ones (Ramos-Galarza *et al.*, 2016; Rojas-Barahona, 2017).

EFs are involved not only on cognitive processes, but also affective and motivational ones, for example, decision-making does not involve just reasoning, but also emotion; they are considered as a dual executive system, proposing the concepts of "cold" and "hot" executive functions, depending on the level that are related to cognitive or emotional aspects, respectively (Montero *et al.*, 2018). Cold EFs (cEFs) are characterized by logical, critical, and conscious analysis of events (Rubia, 2011), including problem-solving, planning, conceptual formation, strategy development and implementation, working memory, verbal reasoning, sequencing, selective attention, resistance to interference, cognitive flexibility, and impulse inhibition (Nejati *et al.*, 2018; Salehinejad *et al.*, 2021). On the other hand, hot EFs (hEFs) are characterized by motivational and/or emotional analysis, as well as the reward associated with actions, involve the coordination of cognition, and emotion/motivation, such as the regulation of social behavior, and decision-making on those events that involve an emotional consequence or appraisal and judgment (Salehinejad *et al.*, 2021).

Figure 1. Relationship cold and hot Executive Functions



There is evidence of a strong correlation between EFs and academic performance; thus, the higher the development of EFs, the higher academic performance; on the contrary, when there is a higher EFs deficit, the lower academic performance, as well as the lower the ability to meet the requirements of environment (Arain *et al.*, 2013; Baars *et al.*, 2015; Besserra-Lagos *et al.*, 2018; Ramos-Galarza and Lozada Montero, 2015). In addition, there are also other positive factors, and cognitive-motivational variables that are key in the learning of college students, such as motivation, self-efficacy, and academic self-concept, future life project, learning strategies (cognitive, metacognitive and support), self-regulated learning, and willingness to study (Bandura, 2006; Cazan, 2012; Marsh and Martin, 2011; Ramos-Galarza *et al.*, 2020).

Self-regulated learning (SRL)

Self-regulated learning (SRL) is composed of cognitive, metacognitive, motivational and affective variables that are able to explain the different ways to organizing actions, monitoring the process, and orientation towards learning goals (Panadero, 2017). SRL management allows the identification and planning of the most appropriate strategies for the learning task to be developed (Dent and Koenka, 2016). Another relevant variable in SRL is how effective the student perceives him/herself to learn a given content, which drives him/her to perform specific actions and plans to control his/her own learning process (Anthonysamy *et al.*, 2020; Bozpolat, 2016; Hernández Barrios and Camargo Uribe, 2017). Also relevant is the definition of goals, those guide the path to follow, the effort put into the task, and self-monitoring performed during the learning process (Panadero and Alonso-Tapia, 2014), which allows controlling the process to generate a change of plans in terms of the defined goals, the activities involved, the required effort and time needed to achieve the proposed goal.

Among the positive factors for academic performance, self-regulation of learning plays an essential role, being considered as a key predictor for lifelong learning, and academic success, and it is important to be acquired since early schooling (Anthonysamy *et al.*, 2020; Dignath and Veenman, 2021; Fernández *et al.*, 2013; Panadero and Alonso-Tapia, 2014; Ramos-Galarza *et al.*, 2020), which implies an active, critical, and reflective process by the student who must be in control of learning by regulating his/her actions to achieve a defined objective (Dignath and Veenman, 2021; Panadero, 2017). Self-regulation of learning is defined by Zimmerman (2002), as a cognitive, metacognitive, affective and behavioral process, where students acquire the skills to plan, monitor, and self-evaluate their academic performance, transforming their mental abilities into academic skills, therefore, this type of strategies are used to help the student learn efficiently, it is a skill that can be developed and mastered (Anthonysamy *et al.*, 2021).

Students who are referred to as "self-regulated" coincide with those who are considered high-achieving and high ability, the traits that mainly possess are as next, large doses of prior knowledge (effective search in his/her memory), use a set of cognitive strategies, and they know where, when, how and why to use them, manage their mental processes towards the achievement of goals, present motivational beliefs, plan and control their time, present greater attempts to participate in the control and regulation of academic tasks, are able to implement volitional strategies, systematically monitor their performance, self-evaluate themselves according to the established goals, and assess the final result of their learning (Carvalho *et al.*, 2016; Ersozlu *et al.*, 2017; García-Marcos *et al.*, 2020; Torrano *et al.*, 2017). Initiative, control, perseverance and mastery of strategies characterize self-regulated students and it is reflected in obtaining better academic results (Fernández *et al.*, 2013).

In addition, research shows that self-regulated students achieve higher performance and prevent failure, since they are characterized by identifying the best plan of action to successfully achieve a learning task, they have intrinsic motivation, high self-efficacy beliefs, use cognitive and metacognitive strategies, and use a diversity of resources to successfully achieve their objectives, through planning, monitoring, and controlling learning, using metacognitive strategies that support the activities of self-regulation, so that the promotion of these skills will improve students' performance and learning (Anthonysamy *et al.*, 2021; DiFrancesca *et al.*, 2016; Dignath and Veenman, 2021; Fonteyne *et al.*, 2017; Sáez *et al.*, 2018; Schober *et al.*, 2015), therefore, all these elements will allow achieving high academic performance and avoiding those difficulties that must be faced when a student is in higher education.

Executive functions are one of the tools or resources of the self-regulation. The executive functions constitutes the foundations of the adaptive and goal-directed behavior, is because of it, that they are a mandatory part of any assessment process (Introzzi and Canet-Juric, 2016). Executive functions and self-regulation of learning differ conceptually and operationally, however, executive functions contribute to the process of self-regulation, three Efs are considered central in self-regulated learning, these are inhibition, cognitive flexibility and working memory, which have an autonomous and independent capacity to modify thoughts, behaviors, and emotions (Juric *et al.*, 2016). There is a directly proportional correlation between the executive functions and self-regulation of learning (Gualpa-Naranjo *et al.*, 2019), where it is evidenced that the higher the levels of performance in executive functions, the higher the level of self-regulation of learning.

In addition, self-regulation of learning involves the articulation of both motivational and cognitive variables (García-Marcos *et al.*, 2020). Regarding cognitive variables, self-regulated students are able to use different strategies according to the context of the task and possesses superior metacognitive skills to set realistic goals, planning the way of achieving those goals, permanently monitor his/her performance, systematically assess the current state of his/her learning to make the necessary changes or adjustments and, finally, reflect globally on the process in order to optimize it in future situations (Hadwin *et al.*, 2011; Zimmerman, 2013).

Method

As a way of investigating the relationship between cEFs and SRLM, it was set as the aim of this study to analyze the relationship between cEFs and SRLM in college students. The hypothesis guiding this research was that there is a positive and statistically significant relationship between SRLM and cEFs. Results were analyzed based on the hypothesis of the existence of a direct and close relationship between both variable with the purpose of establishing the basis that allow to comprehend how college students are learning and which variables influence it, thus, develop supporting strategies at the higher educational system that helps to improve college students' academic performance.

Participants

Sample was non-probabilistic by convenience composed by n = 379 college students from pedagogy careers. The sample included students aged between 17 and 34 years (M = 19.82, SD = 2.41), 243 males, and 136 females, representing the 64.1%, and 35.9%, respectively. The participants of this research were informed about the purposes and characteristics this study, and its acceptance to participate was written down in an informed consent, allowing, as well, the use of the data obtained. The procedure of this investigation was approved by the Ethics Committee for research on humans of the Pontifical Catholic University of Ecuador with the code 2019-58-EO.

Instruments

– *Scale to assess the Executive Functions (EFECO)* in its self-reported format (Ramos-Galarza *et al.*, 2018), which was developed based on the one designed by Andrés García Gómez, for parents and teachers in Ecuadorian context (García Gómez, 2015). The scale is made up of 42 items, divided in 9 subscales, inhibitory control, verification, monitoring, organization of materials, cognitive flexibility, emotional control, working memory, initiative and planning, their aim are to assess cold EFs (Salehinejad *et al.*, 2021) through the analysis of narrative-based statements focused on positive ability. Preliminary studies in Ecuador corroborate the utility of this instrument showing linguistic validity, high internal consistence and discrimination capacity (García Gómez, 2015; Ramos-Galarza *et al.*, 2016, 2018). In this application, adequate indicators of internal consistency as measured by Cronbach's α .95; Guttman's β .95; and McDonalds' Omega ω .95, were obtained.

– *Self- Regulated Learning Management Scale* (Ramos-Galarza *et al.*, 2019) made up of 19 items distributed in 4 subscales in its self-reported format, that allow to know self-management of learning, academic performance perception, conscious motivation strategies for learning, and deep learning strategies. Items are answered on a five-point Likert-type scale (1= totally disagree; 2= slightly disagree; 3= neither agree nor disagree; 4= slightly agree; 5= strongly agree). Although this instrument has not been validated in Chile, for this application it was analyzed its internal consistency and reliability in this population, obtaining adequate indicators of the construct by means of a confirmatory factor analysis (χ^2 = 459.9, df = 146, p-value<.000; RMSE = .075 [.068, .083]; CFI = .986; TLI = .983). Additionally, internal consistency was analyzed, obtaining appropriate indicators at the general level (Cronbach's α .90; Guttman's β .91; and McDonald's Omega ω .93). Also, at the dimension level, adequate indicators of internal consistency are obtained given by: self-management of learning (Cronbach's α .82; Guttman's β .82; and McDonald's Omega ω .89); conscious motivation strategies for learning (Cronbach's α .83; Guttman's β .81; and McDonald's Omega ω .91); perceived academic performance (Cronbach's α .63; Guttman's β .63; and McDonald's Omega ω .66); and deep learning strategies (Cronbach's α .79; Guttman's β .79; and McDonald's Omega ω .81).

Data Processing

This investigation was a quantitative and cross-sectional study, with a correlational, descriptive, and inferential approach. Accordingly, Pearson's correlation analysis was carried out to analyze the hypothesis of the existence of a relationship between cEFs and SRLM, subsequently, an analysis of variance (ANOVA – MANOVA) was conducted. Finally, there was executed a logistic regression to analyze the dimensions' predictive power of the cEFs scale on the SRLM.

In the logistic regression model, students with SRLM scores above the cut-off point are identified by $Y = 1$. Thus, starting from a logistic distribution as proposed by Greene (2012), the binary logit model was estimated that allows modeling the change in the probability that a student presents a score higher than the cut-off point in SRLM, according to the equation (1),

$$Prob(Y = 1 \mid \chi) = \frac{e^{\chi'\beta}}{1 + e^{\chi'\beta}} \tag{1}$$

Where, $Y = 1$ belongs to an individual with SRLM score above the cut-off point conditional on χ that incorporates the dimensions of the cEFs scale. The model was estimated through the maximum likelihood method, and results show the effects in terms of average marginal effects. Every estimation and statistical processing were performed using Rstudio software.

Results

Descriptive analysis

A descriptive analysis of the variables under studio were executed, it is possible to observe that skewness and kurtosis are within values that allow us to affirm an univariate normality, and similar mean and median values, reflecting the homogeneity of the measurements (Table 1).

Table 1. Statistical summary

VARIABLE	N	M	SD	ME	MIN.	MAX.	S	K
cEFs Scale (Total)	379	169.56	21.15	172	66	210	-.83	1.32
SRLM Scale (Total)	379	75.33	10.94	76	31	95	-.76	.75
Inhibitory control	379	23.92	3.52	24	12	30	-.57	.21
Verification	379	12.58	2.09	13	3	15	-1.09	1.86
Monitoring	379	21.42	2.75	22	6	25	-1.21	2.80
Organization of materials	379	16.88	3.05	18	4	20	-1.26	1.54
Cognitive flexibility	379	16.17	2.53	17	4	20	-.96	1.81
Emotional control	379	18.99	4.28	20	5	25	-.82	.46
Working memory	379	19.80	3.06	20	10	25	-.60	.23
Iniciatitive	379	20.69	3.03	21	7	25	-.94	1.35
Planning	379	19.11	3.40	19	7	25	-.53	.06
Self-management of learning	379	24.20	3.97	24	7	30	-.69	.70
Conscious motivation strategies for learning	379	20.99	3.57	22	5	25	-1.19	2.10
Perceived academic performance	379	14.70	2.72	15	4	20	-.61	.86
Deep learning strategies	379	15.44	3.14	16	4	20	-.79	.99

Note. N: observation number; M: mean; SD: standard deviation, Me: median, Min.: minimum value, Max.: maximum value, S: skewness, and K: kurtosis.

Correlation between cold Executive functions and Self-regulated learning management

At first, regarding the relationship between the cEFs and SRLM scales (both in total), it is possible to observe between these a strong positive relationship of $r = .74$, indicating that those students who present higher scores on the cEFs scale, also obtain higher scores on the SRLM scale.

Secondly, a positive and strong correlation is shown in the cEF of planning $r = .71$, which, at the same time, is strongly related to the dimension of initiative $r = .68$, working memory $r = .64$, verification $r = .61$, and monitoring $r = .60$. In addition, a medium-high correlation is observed with the cognitive flexibility dimension $r = .58$.

Thirdly, it is observed a strong positive correlation between the cEFs scale and some dimension of the SRLM scale. Thus, it can be addressed that there is a positive correlation between cEF and SMRL $r = .73$. On the other hand, there is a positive and strong relationship with the deep learning strategies dimension $r = .61$.

Fourth, when the relationship between the dimensions of the cEFs scale is analyzed, it can be noted that there is a strong a positive relationship with the dimensions that make up the SRLM scale. In example, the relationship between the dimensions planning and Self-management of learning is positive with a magnitude of $r = .71$. Also, it is highlighted the positive relationship between planning and deep learning strategies $r = .67$. The details of the bivariate correlations can be reviewed in Table 2.

Table 2. Correlation matrix between the Executive Functions scale and the Learning management scale

	VARIABLE	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	cEFs Scale (Total)	1													
2	SRLM Scale (Total)	.74**	1												
3	Inhibitory control	.81**	.50**	1											
4	Verification	.69**	.61**	.50**	1										
5	Monitoring	.76**	.60**	.48**	.55**	1									
6	Organization of materials	.64**	.50**	.46**	.47**	.42**	1								
7	Cognitive flexibility	.77**	.58**	.57**	.51**	.61**	.37**	1							
8	Emotional control	.67**	.35**	.55**	.24**	.39**	.26**	.46**	1						
9	Working Memory	.84**	.64**	.72**	.56**	.61**	.45**	.63**	.42**	1					
10	Initiative	.86**	.68**	.61**	.58**	.70**	.45**	.66**	.54**	.68**	1				
11	Planning	.84**	.71**	.60**	.62**	.59**	.56**	.60**	.40**	.70**	.71**	1			
12	Self-management of learning	.73**	.88**	.47**	.60**	.61**	.58**	.55**	.31**	.62**	.65**	.71**	1		
13	Conscious motivation strategies for learning	.51**	.79**	.36**	.41**	.37**	.29**	.42**	.31**	.45**	.50**	.46**	.53**	1	
14	Perceived academic performance	.54**	.77**	.30**	.42**	.55**	.28**	.47**	.28**	.49**	.53**	.45**	.62**	.51**	1
15	Deep learning strategies	.61**	.80**	.47**	.53**	.43**	.44**	.46**	.23**	.53**	.53**	.67**	.67**	.51**	.44**

Note. Pearson's correlations, where * indicates p < .05. ** indicates p < .01. N = 379.

Mean differences between cEFs and SRLM

Since a direct and strong relationship between cEFs (its dimensions) and SRLM was found, a MANOVA procedure was performed using the SRLM recoded into achievement levels (Low <= 69.00; Medium = 70.00-84.00; High >= 85.00 according to quartiles 1 and 3). At first, Mahalanobis distances were analyzed to determine the presence of outlier data and setting a cut-off threshold, which reduced the number of the initial sample to n = 349. The assumption of homoscedasticity of variances and covariances was tested, rejecting the hypothesis of equality (Box's M-test X^2 = 152.56, df = 90, p < .05), so, results were analyzed using Pillai's test robust to heteroscedasticity.

On the other hand, the MANOVA test indicated statistically significant differences between groups (Pillai's F (18,678) = 13.00, p < .001, ηp^2 = .26). Additionally, univariate analyses (ANOVA) indicated differences between all groups in the cEFs of: Inhibitory control (F (2,346) = 29.25, p < .001, ηp^2 = .14), Verification (F (2,346) = 62.69, p < .001, ηp^2 = .26), Monitoring (F (2,346) = 72.69, p < .001, ηp^2 = .29), Organization of materials (F (2,346) = 32.72, p < .001, ηp^2 = .15), Cognitive flexibility (F (2,346) = 50.33, p < .001, ηp^2 = .22), Emotional control (F (2,346) = 17.97, p < .001, ηp^2 = .09), Working memory (F (2,346) = 67.38, p < .001, ηp^2 = .28), Initiative (F (2,346) = 97.21, p < .001, ηp^2 = .36), and Planning (F (2,346) = 121.7, p < .001, ηp^2 = .41). Table 3 shows the results in descriptive terms and group mean differences.

Table 3. Descriptive of Executive Functions by achievement level and differences of means

cFEs Scale	SRLM SCALE (TOTAL)						DIFFERENCES		
	Low (n=88)		*Medium (n=174)*		*High (n=87)*		ANOVA		
	M	SD	M	SD	M	SD	L-M	L-H	M-H
Inhibitory control	22.41	3.22	24.26	3.15	25.93	2.64	1.85**	3.52**	1.67**
Verification	11.41	1.85	12.87	1.61	14.06	1.11	1.46**	2.65**	1.19**
Monitoring	19.61	2.28	21.93	2.14	23.23	1.43	2.31**	3.62**	1.30**
Organization of materials	15.47	3.01	17.36	2.55	18.48	1.76	1.90**	3.02**	1.12**
Cognitive flexibility	14.74	2.02	16.63	2.04	17.67	1.76	1.89**	2.93**	1.04**
Emotional control	17.65	4.13	19.25	4.01	21.10	3.01	1.60**	3.46**	1.86**
Working memory	17.89	2.55	20.25	2.50	22.10	2.07	2.37**	4.22**	1.85**
Initiative	18.66	2.36	21.22	2.18	23.11	1.73	2.57**	4.46**	1.89**
Planning	16.42	2.52	19.59	2.57	22.11	1.98	3.17**	5.69**	2.53**

Note. * post-hoc Turkey test * indicates p < .05. ** indicates p < .01; M: mean; SD: standard deviation. L=low; M= medium; H= High. n = 349.

Predictive Value of cEFs on SRLM

A logistic regression to weight the predictive value of each factor associated to the Executive functions on the score obtained on the SRLM scale (Total) was used. Table 4 shows the results for the traditional multiple regression model, estimated by ordinary least squares (OLS), its dependent variable is the total obtained on the SRLM scale. In addition, it shows the marginal effects (predictive value) using two cut-off points on the SRLM scale score set above the mean, and one deviation above the mean.

Table 4. Regression Model (OLS) and marginal effects - logit model

		LOGIT MODEL (MARGINAL EFFECTS)	
	OLS	CUT-OFF POINT ABOVE THE MEAN	CUT-OFF POINT ONE DEVIATION ABOVE THE MEAN
Emotional control - EC	-.356* (0.162)	.001 (0.006)	.010 (.006)
Inhibitory control - IC	.805** (0.235)	-.010 (0.009)	-.003 (.008)
Cognitive flexibility - CF	.273 (0.193)	.007 (0.012)	-.010 (.011)
Initiative - IN	.362* (0.143)	.015 (0.012)	**.033** (.012)**
Monitoring - MO	.389 (0.205)	**.026* (0.011)**	.010 (.011)
Working Memory - WM	-.030 (0.107)	.021 (0.011)	.005 (.009)
Organization of materials - OM	.576** (0.202)	**.019* (0.008)**	.003 (.009)
Planning - PL	.761** (0.209)	**.037** (0.01)**	**.022* (.009)**
Verification - VF	.895** (0.176)	.024 (0.013)	**.042** (.014)**
Number of observations	379	379	379
Adjunsted R^2	.613		
McFadden's R^2		.395	.357
ROC		.728	.754

Note. * Indicates p < .05. ** indicates p < .01; the standard deviations of parameters or marginal effects are shown in parenthesis as corresponding. The VIF collinearity test is used, showing that these values are under 5 (IC = 2.6; VF = 1.9; MO = 2.3; OM = 1.6; CF = 2.2; EC = 1.7; WM = 3.1; IN = 3.3; PL = 2.9).

In the OLS column of Table 4, the multiple regression model considering the total score on SRLM scale (F (9,369) =67.660, p<.001) is shown. While, the following columns show the marginal effects, it means, the effects on the probability that a student who is above the mentioned cut-off points on SRML given his/her level of achievement on the cEFs scale. Both models show appropriate levels of fit with McFadden's R^2 above .35, and ROC above .70.

Considering the model above the mean as the cut-off point, it is possible to indicate that the larger effect is predicted by the cEF of Planning (Δ ≈ 3.7%). Meaning that, for each additional point obtained by a student in this EF dimension, the probability of presenting a SRLM score above the mean increases by 3.7%. Significant effects are additionally observed in Monitoring (Δ ≈ 2.6%), and Planning (Δ ≈ 1.9%) cEFs. If the model is considered on one deviation above the mean on SRLM as the cut-off point, the largest significant effect is predicted by the EF of Verification (Δ ≈ 4.2%), followed by Initiative (Δ ≈ 3.3%), and again, Planning (Δ ≈ 2.2%).

Discussion and conclusions

University context is increasingly open and diverse, precising new teaching competences, as well as the students' autonomous management of learning, to self-regulate their learning process, designing plans, anticipating solutions and results, controlling thoughts, emotions, and actions. These skills are directly related in their operative functioning with higher cognitive processes such as attentional control, working memory, inhibitory control, cognitive flexibility, planning and problem-solving (Caffarena Barcenilla and Rojas-Barahona, 2019; Posner and Rothbart, 2000).

The aim of this study was to analyze the relationship between cEFs and SRLM, in this sense, it was found empirical evidence of the relationship between cEFs and SRLM in college students, and the hypothesis that there is a positive and statistically significant relationship between both constructs is proven. This relationship is reported as a direct and strong correlation, with a medium effect when its variance is analyzed. These results coincide with previous research stating that, as a set, the cEFs and the process of self-regulation of learning contribute significantly to the student's ability to successfully manage his/her own behavior, thoughts and emotions, which influences positively in their academic performance and, consequently, the achievement of higher learning and academic success (Anthonysamy *et al.*, 2020; García-Marcos *et al.*, 2020, 2020; Juric *et al.*, 2016; Ramos-Galarza *et al.*, 2020).

In general terms, it was observed that the SRLM dimensions are most strongly related to the cEFs self-management of learning and deep learning strategies. Both are closely linked to the cEF planning, it can be explained by the skills that are involved in learning management, which are dependent on the ability of planning in the learning process. In this sense, it was showed that the cEF that predicts in a good fit the SRLM is the cEF of planning. The above means that, a better development of this cEF increases the probability that students present high levels in the skills to manage their own learning process. It is because self-management for learning refers to the active student's intervention in planning, execution and evaluation of learning (Brookfield, 2004). It is also related to self-monitoring and motivation for learning (Cerda and Saiz, 2018), which are main elements involved in the effective planning of any learning process.

Another aspect related to self-management of learning is the ability to autonomously define learning goals and needs, and, at the same time, to determine strategies to achieve the proposed goals (Dent and Koenka, 2016; Panadero, 2017; Pérez-Villalobos *et al.*, 2017). In this sense, these are skills that are closely related to the cEF of planning, as demonstrated in this study, since for the management of self-regulated learning it is required to plan and monitor the process permanently, so as, to make the most adequate decisions and change the working plan if necessary. On the other hand, learning strategies are an organized and intentional set of procedures that allow to accomplish academic objectives effectively (Gargallo, *et al.*, 2007). Deep learning, from the self-regulation approach refers to the set of processes with the purpose of defining personal goals, establishing strategies according to the task, monitor the actions that are being developed, organize the physical environment (place, lighting, noise, materials, etc.), as well as social (number of people, willingness to the task), in the way of completing a task within the time previously established (time control), assessing permanently the development of the task and defining new action plans if necessary (Zimmerman, 2013). In this sense, deep learning strategies require high levels of organization and planning of the strategies involved in the learning task, hence, these are closely related.

Regarding the SRLM, this study demonstrates that the strongest relationship is with the working memory, initiative, and planning cEFs. This is consistent with the MANOVA analysis performed, where the main differences and effect sizes between students with low and high learning management occur in the working memory, initiative, and planning cEFs. Also, these results are consistent to the logistic regression that shows that the cEF of planning and initiative predict high levels of SRML in students.

The above is consistent with previous research that show that the strong association with working memory, is given because this skill is related to essential processes for the achievement of learning, it is central to the adequate performance reading comprehension skills, problem-solving, among others academic skills (Fonseca *et al.*, 2016; López, 2014; Risso *et al.*, 2015), which ensure an adequate learning management at any educational level. The cEF of initiative is strongly related to SRLM, since initiative guides the learner to autonomously and personal manage the actions that he/she believes will best solve the proposed task (Brookfield, 2004), which is necessary for learning to be effectively self-regulated internally by the student, and not by external factors. Finally, planning, as it was mentioned before, is a cEF that is involved in SRLM since it is required for the management of learning and also in the use of strategies for deep learning (Pérez-Villalobos *et al.*, 2017).

It has also been shown that initiative, control, perseverance and mastery of learning strategies characterize self-regulated students and it is reflected in better academic results (Fernández *et al.*, 2013). Also, planning and control or maintenance of effort and time are considered as superior mental skills, that, will influence positively the academic environment of college students (Gualpa-Naranjo *et al.*, 2019).

As summary, the purpose of this study was to analyze the relationship between cEFs and SRLM. It is possible to conclude that there is a relationship between the variables, thus, university processes, especially in the first years that involve a high adaptation process, there should be considered specific plans to train the cEFs and SRLM, in order to ensure, on one hand, students' academic performance, and, on the other hand, university life to be developed positively and with lower stress levels that adaptation to university life produces in a large number of students. In this sense, to early detect deficit in these variables it must be included characterization evaluations that measures cEFs and SRLM and thus, include its results into the inclusive support programs provided by universities.

Some limitations of this study that allow projecting future research refer to the fact that the sample was by convenience, so it is suggested to study these variables on a larger, heterogeneous, and generalized sample of participants for greater representativeness. On the other hand, this study only contemplated the analysis and relationship of cold executive functions with self-regulated learning, being necessary to include hot executive functions analysis in future research.

Finally, for future investigation it is arisen the need to search the effect of both cEFs, and SRLM on students' academic performance, especially in those critical subjects in each career, which influence the rates of progression, retention, and graduation, to further deepen the relationship between cEFs and SRLM to define more comprehensive strategies when monitoring and guiding college students.

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References

Anthonysamy, L., Choo, K. A., and Hin, H. S. (2021). Investigating self-regulated learning strategies for digital learning relevancy. *Malaysian Journal of Learning and Instruction*, *18*(1), 29-64. https://doi.org/10.32890/mjli2021.18.1.2

Anthonysamy, L., Koo, A. C., and Sh, H. (2020). Self-regulated learning strategies and non-academic outcomes in higher education blended learning environments: A one decade review. *Education and Information Technologies*, *25*. https://doi.org/10.1007/s10639-020-10134-2

Arain, M., Haque, M., Johal, L., Mathur, P., Nel, W., Rais, A., Sandhu, R., and Sharma, S. (2013). Maturation of the adolescent brain. *Neuropsychiatric Disease and Treatment*, *9*, 449-461. https://doi.org/10.2147/NDT.S39776

Baars, M. A. E., Nije Bijvank, M., Tonnaer, G. H., and Jolles, J. (2015). Self-report measures of executive functioning are a determinant of academic performance in first-year students at a university of applied sciences. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01131

Bandura, A. (2006). Toward A Psychology of Human Agency. *Perspectives on Psychological Science*, *1*. https://doi.org/10.1111/j.1745-6916.2006.00011.x

Bausela Herreras, E. (2014). Funciones ejecutivas: Nociones del desarrollo desde una perspectiva neuropsicológica. *Acción Psicológica*, *11*(1), 21-34. https://doi.org/10.5944/ap.1.1.13789

Besserra-Lagos, D., Lepe-Martínez, N., and Ramos-Galarza, C. (2018). Las funciones ejecutivas del lóbulo frontal y su asociación con el desempeño académico de estudiantes de nivel superior. *Revista Ecuatoriana de Neurología*, *27*(3), 51-56.

Binkley, M., Erstad, O., Herman, J., Raizen, S., Ripley, M., Miller-Ricci, M., and Rumble, M. (2012). Defining Twenty-First Century Skills. En P. Griffin, B. McGaw, and E. Care (Eds.), *Assessment and Teaching of 21st Century Skills* (pp. 17-66). Springer Netherlands. https://doi.org/10.1007/978-94-007-2324-5_2

Bozpolat, E. (2016). Investigation of the Self-Regulated Learning Strategies of Students from the Faculty of Education Using Ordinal Logistic Regression Analysis. *Educational Sciences: Theory & Practice*, *16*, 301-318. https://doi.org/10.12738/estp.2016.1.0281

Brookfield, S. (2004). Self-Directed Learning. En A. DiStefano, K. E. Rudestam and R. J. Silverman (Eds.), *Encyclopedia of Distributed Learning* (pp. 397-399). Sage.

Caffarena Barcenilla, C., and Rojas-Barahona, C. A. (2019). La Autorregulación en la Primera Infancia: Avances Desde la Investigación. *Revista Ecuatoriana de Neurología*, *28*(2), 37-49.

Carvalho, P. F., Braithwaite, D. W., Leeuw, J. R. de, Motz, B. A., and Goldstone, R. L. (2016). An In Vivo Study of Self-Regulated Study Sequencing in Introductory Psychology Courses. *PLOS ONE*, *11*(3), e0152115. https://doi.org/10.1371/journal.pone.0152115

Cazan, A.-M. (2012). Self regulated learning strategies-Predictors of academic adjustment. *Procedia-Social and Behavioral Sciences*, *33*, 104-108. https://doi.org/10.1016/j.sbspro.2012.01.092

Cerda, C., and Saiz, J. L. (2018). Aprendizaje autodirigido del saber pedagógico con tecnologías digitales. Generación de un modelo teórico en estudiantes de pedagogía chilenos. *Perfiles Educativos*, *40*(162), 138-157. https://doi.org/10.22201/iisue.24486167e.2018.162.58756

Dent, A. L., and Koenka, A. C. (2016). The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review*, *28*(3), 425-474. https://doi.org/10.1007/s10648-015-9320-8

DiFrancesca, D., Nietfeld, J. L., and Cao, L. (2016). A comparison of high and low achieving students on self-regulated learning variables. *Learning and Individual Differences*, *45*, 228-236. https://doi.org/10.1016/j.lindif.2015.11.010

Dignath, C., and Veenman, M. V. J. (2021). The Role of Direct Strategy Instruction and Indirect Activation of Self-Regulated Learning-Evidence from Classroom Observation Studies. *Educational Psychology Review*, *33*(2), 489-533. https://doi.org/10.1007/s10648-020-09534-0

Ersozlu, Z., Nietfeld, J., and Huseynova, L. (2017). Predicting preservice music teachers' performance success in instrumental courses using self-regulated study strategies and predictor variables. *Music Education Research*, *19*, 123-132. https://doi.org/10.1080/14613808.2015.1092508

Fernández, E., Bernardo, A., Suárez, N., Cerezo, R., Núñez, J. C., and Rosário, P. (2013). Predicción del uso de estrategias de autorregulación en la educación superior: Un análisis a nivel individual y de contexto. *Anales de Psicología*, *29*(3), 865-875. https://doi.org/10.6018/analesps.29.3.139341

Fonseca, G., Rodríguez, L., and Parra, J. (2016). Relación entre funciones ejecutivas y rendimiento académico por asignaturas en escolares de 6 a 12 años. *Hacia la Promoción de la Salud*, *21*(2), 18. https://doi.org/10.17151/hpsal.2016.21.2.4

Fonteyne, L., Duyck, W., and De Fruyt, F. (2017). Program-specific prediction of academic achievement on the basis of cognitive and non-cognitive factors. *Learning and Individual Differences*, *56*, 34-48. https://doi.org/10.1016/j.lindif.2017.05.003

Gallegos, J. A., Campos, N. A., Canales, K. A., and González, E. N. (2018). Factores Determinantes en la Deserción Universitaria. Caso Facultad de Ciencias Económicas y Administrativas de la Universidad Católica de la Santísima Concepción (Chile). *Formación universitaria*, *11*(3), 11-18. https://doi.org/10.4067/S0718-50062018000300011

García Gómez, A. (2015). Desarrollo y validación de un cuestionario de observación para la evaluación de las funciones ejecutivas en la infancia. *Revista Intercontinental de Psicología y Educación*, *17*(1), 141-162. https://www.redalyc.org/pdf/802/80242935008.pdf

García-Marcos, C. J., López-Vargas, O., and Cabero-Almenara, J. (2020). Autorregulación del aprendizaje en la Formación Profesional a Distancia: Efectos de la gestión del tiempo. *Revista de Educación a Distancia (RED)*, *20*(62). https://doi.org/10.6018/red.400071

Gargallo, B., Suárez, J., and Ferreras, A. (2007). Estrategias de aprendizaje y rendimiento académico en estudiantes universitarios. *Revista de Investigación Educativa*, *25*(2), 421-441.

Gilbert, S. J., and Burgess, P. W. (2008). Executive function. *Current Biology: CB*, *18*(3), R110-114. https://doi.org/10.1016/j.cub.2007.12.014

Gualpa-Naranjo, K., Valencia-Paredes, D., Barrera-Sandoval, D., Robles-Luna, D., Portocarrero-Montoya, K., Rodríguez-Armijos, R., and Ramos-Galarza, C. A. (2019). Las funciones ejecutivas y la regulación del aprendizaje de universitarios. *Wimb Lu*, *14*(1), 127-137. https://doi.org/10.15517/wl.v14i1.36906

Hadwin, A., Järvelä, S., and Miller, M. (2011). Self-regulated, co-regulated, and socially share regulation of learning. In B. J. Zimmerman and D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 65-84). Routledge/Taylor & Francis Group.

Hernández Barrios, A., and Camargo Uribe, A. (2017). Adaptación y validación del Inventario de Estrategias de Autorregulación en estudiantes universitarios. *Suma Psicológica*, *24*(1), 9-16. https://doi.org/10.1016/j.sumpsi.2017.02.001

Introzzi, I., and Canet-Juric, L. (2016). *¿Quién dirige la batuta? Funciones Ejecutivas: Herramientas para la regulación de la mente, la emoción y la acción*. EUDEM.

Juric, L. C.-, Introzzi, I., Andrés, M. L., and Stelzer, F. (2016). La contribución de las Funciones Ejecutivas a la Autorregulación. *Cuadernos de Neuropsicología / Panamerican Journal of Neuropsychology*, *10*(2), Article 2. https://www.cnps.cl/index.php/cnps/article/view/238

López, M. (2014). Desarrollo de la Memoria de Trabajo y Desempeño en Cálculo Aritmético: Un Estudio Longitudinal en Niños. *Electronic Journal of Research in Education Psychology*, *12*(1), 171-190. https://doi.org/10.14204/ejrep.32.13103

Marsh, H., and Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. *The British Journal of Educational Psychology*, *81*, 59-77. https://doi.org/10.1348/000709910X503501

Montero, L. D., Fontana, E., Querejeta, A. N., Farías Sarquís, Y., Moreno, M. A., Roqué, D., Marengo, L. and Cabrera, M. E. (2018). Relación entre Funciones Ejecutivas Frías, Cálidas e Inteligencia. *Anuario de Investigaciones de la Facultad de Psicología*, *3*(2), 234-247.

Nejati, V., Salehinejad, M. A., and Nitsche, M. A. (2018). Interaction of the Left Dorsolateral Prefrontal Cortex (l-DLPFC) and Right Orbitofrontal Cortex (OFC) in Hot and Cold Executive Functions: Evidence from Transcranial Direct Current Stimulation (tDCS). *Neuroscience*, *369*, 109-123. https://doi.org/10.1016/j.neuroscience.2017.10.042

Panadero, E. (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00422

Panadero, E., and Alonso-Tapia, J. (2014). ¿Cómo autorregulan nuestros alumnos? Modelo de Zimmerman sobre estrategias de aprendizaje. *Anales de Psicología*, *30*, 450-462. https://doi.org/10.6018/analesps.30.2.167221

Pérez-Villalobos, C. E., Fasce-Henry, E. A., Ortega-Bastidas, J. A., Ortiz-Moreira, L. E., Bastías-Vega, N., Bustamante-Durán, C. E., Ibáñez-Gracia, P., Márquez-Urrizola, C. G., Delgado-Rivera, M., and Glaría-López, R. (2017). ¿Cómo han cambiado los estudiantes que ingresan a medicina? Aprendizaje autodirigido y antecedentes académicos de las cohortes 2010 a 2014 de una universidad tradicional. *Revista Médica de Chile*, *145*(7), 934-940. https://doi.org/10.4067/s0034-98872017000700934

Pineda, D. (2000). La función ejecutiva y sus trastornos. *Revista de Neurología*, *30*(8), 764-768. https://doi.org/10.33588/rn.3008.99646

Posner, M. I., and Rothbart, M. K. (2000). Developing mechanisms of self-regulation. *Development and Psychopathology*, *12*(3), 427-441. https://doi.org/10.1017/S0954579400003096

Ramos-Galarza, C. A., Jadán-Guerrero, J., García Gómez, A., and Paredes, L. (2016). Propuesta de la Escala Efeco Para Evaluar las Funciones Ejecutivas en Formato de Auto-Reporte. Proposal of the Efeco Scale to Assess Executive Functions in Self-Report Format. *CienciAmérica*, 5, 104-109.

Ramos-Galarza, C. A., Lepe-Martínez, N., del Valle, M., Acosta-Rodas, P., and Ortiz-Granja, D. N. (2019). *Escala de Gestión del Aprendizaje Autorregulado (documento de trabajo)*. Universidad Católica del Maule, Chile, Pontificia Universidad Católica del Ecuador, Ecuador y Universidad de Antofagasta, Chile.

Ramos-Galarza, C. A., and Lozada Montero, J. D. (2015). ¿Los Estudiantes Universitarios Tienen Dificultades Neuropsicológicas en el Control de Impulsos o en su Monitorización? *CienciAmérica*, 4, 28-34.

Ramos-Galarza, C. A., Rubio, D., Ortiz, D., Acosta, P., Hinojosa, F., Cadena, D., and López, E. (2020). Autogestión del aprendizaje del universitario: Un aporte en su construcción teórica. *Revista Espacios*, *41*(18). https://www.revistaespacios.com/a20v41n18/20411816.html

Ramos-Galarza, C. A., Villegas, C., Ortiz, D., García, A., Bolaños, M., Acosta, P., Lepe, N., del Valle, M., and Ramos, V. (2018). *Evaluación de las Habilidades de la Corteza Prefrontal: La Escala Efeco II-VC y II-VR. Revista Ecuatoriana de Neurología*, *27*(3), 36-42.

Risso, A., García, M., Durán, M., Brenlla, J., Peralbo, M., and Barca, A. (2015). Un análisis de las relaciones entre funciones ejecutivas, lenguaje y habilidades matemáticas. *Revista de Estudios e Investigación en Psicología y Educación*, *Extra 9*, 73-78. https://doi.org/10.17979/reipe.2015.0.09.577

Rojas-Barahona, C. (2017). *Funciones ejecutivas y Educación: Comprendiendo habilidades clave para el aprendizaje*. EdicionesUC.

Rubia, K. (2011). "Cool" inferior frontostriatal dysfunction in attention-deficit/hyperactivity disorder versus "hot" ventromedial orbitofrontal-limbic dysfunction in conduct disorder: A review. *Biological Psychiatry*, *69*(12), e69-87. https://doi.org/10.1016/j.biopsych.2010.09.023

Sáez, F. M., Díaz, A. E., Panadero, E., and Bruna, D. V. (2018). Revisión Sistemática sobre Competencias de Autorregulación del Aprendizaje en Estudiantes Universitarios y Programas Intracurriculares para su Promoción. *Formación Universitaria*, *11*(6), 83-98. https://doi.org/10.4067/S0718-50062018000600083

Salehinejad, M. A., Ghanavati, E., Rashid, M. H. A., and Nitsche, M. A. (2021). Hot and cold executive functions in the brain: A prefrontal-cingular network. *Brain and Neuroscience Advances*, *5*, 23982128211007770. https://doi.org/10.1177/23982128211007769

Santa-Cruz, C., and Rosas, R. (2017). Mapping of Executive Functions / *Cartografía de las Funciones Ejecutivas*. *Studies in Psychology*, *38*(2), 284-310. https://doi.org/10.1080/02109395.2017.1311459

Schober, B., Klug, J., Jöstl, G., Spiel, C., Dresel, M., Steuer, G., Schmitz, B., and Ziegler, A. (2015). Gaining substantial new insights into university students' self-regulated learning competencies: How can we succeed? *Zeitschrift für Psychologie*, *223*(1), 64-65. https://doi.org/10.1027/2151-2604/a000201

Tirapu Ustárroz, J., Cordero Andrés, P., Luna Lario, P., and Hernáez Goñi, P. (2017).

Propuesta de un modelo de funciones ejecutivas basado en análisis factoriales. *Revista de Neurología*, *64*(02), 75. https://doi.org/10.33588/rn.6402.2016227

Torrano, F., Fuentes, J. L., and Soria, M. (2017). Aprendizaje autorregulado: Estado de la cuestión y retos psicopedagógicos. *Perfiles Educativos*, *39*(156), 160-173.

Zimmerman, B. J. (2002). Becoming a Self-Regulated Learner: An Overview. *Theory Into Practice*, *41*(2), 64-70. https://doi.org/10.1207/s15430421tip4102_2

Zimmerman, B. J. (2013). From cognitive modeling to self-regulation: A social cognitive career path. *Educational Psychologist*, *48*(3), 135-147. https://doi.org/10.1080/00461520.2013.794676

Zuñiga-Vilches, M., Vergara-Morales, J., Pérez-Villalobos, M.-V., and Díaz-Mujica, A. (2020). Factores cognitivo-motivacionales relacionados con el ajuste a la vida universitaria de estudiantes chilenos. *Escritos de Psicología*, *13*(2), 71-79. https://doi.org/10.24310/espsiescpsi.v13i2.12411