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Deep learning self-regulation strategies: Validation of a situational model and its questionnaire☆

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A R T I C L E   I N F O

A B S T R A C T

Measuring self-regulated learning is crucial to improve our educational interventions. Self-report has been the major data collection method and a number of questionnaires exist. Importantly, the vast majority of the questionnaires are constructed from general theoretical models. Our aim was to develop a model and its questionnaire –i.e. *Deep Learning Strategies questionnaire*- to investigate how students regulate their learning strategies in more realistic learning situations. Four scales were created: (1) *Basic learning self-regulation strategies*; (2) *Visual elaboration and summarizing strategies*; (3) *Deep information processing strategies*; and (4) *Social learning self-regulation strategies*. A total of 601 higher education students formed the sample. We analyzed, first, the internal validity of the questionnaire. Three structural models were tested: (M1) mono-factor; (M2) scales correlate among them freely, and (M3) the scales are indicators of a general construct. The latter model showed a slight better fit. Additionally, a path analysis was carried out to study the degree in which the use of the *Deep learning strategies* depends on personal factors and is associated to performance. It was found that the use depends directly and positively on *learning goal orientation,* on the self-messages defining the *self-regulation style of emotion and motivation focused on learning*, and on *effort.* Besides, these two last variables convey the effect of *self-efficacy* that, at the same time, affects *effort*. Academic performance, depends positively on *effort* but negatively to the use of *deep learning strategies*. It is hypothesized this negative relationship is due to the method of measurement of academic performance.

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Estrategias de aprendizaje profundas: Validación de un modelo situacional y su cuestionario

R E S U M E N

Medir el aprendizaje autorregulado es fundamental para mejorar nuestras intervenciones educativas. Los cuestionarios de autoinforme han sido el principal método para su evaluación, con la mayoría de instrumentos construidos a partir de "modelos teóricos" generales. Frente a estos, este estudio valida un modelo basado en situaciones realistas de aprendizaje observadas en los alumnos. El *Cuestionario de estrategias profundas de aprendizaje,* tiene cuatro escalas: (1) *Estrategias básicas de autorregulación del aprendizaje*; (2) *Estrategias de elaboración visual y de resumen*; (3) *Estrategias de procesamiento profundo de información*; y (4) *Estrategias sociales de autorregulación del aprendizaje*. Participan 601 estudiantes

universitarios. Primero, se ha analizado la validez interna del cuestionario, contrastando tres modelos: (M1) monofactorial; (M2) cuatro grupos de estrategias correlacionando libremente entre ellas; (M3) el factor de cada grupo de estrategias es indicador de un constructo latente general, modelo que resulta ligeramente mejor ajustado. Segundo, se ha realizado un análisis de rutas para estudiar si el uso de las *estrategias de aprendizaje profundo* depende de factores personales y predice el rendimiento. Se ha encontrado que depende directa y positivamente de la *orientación hacia el aprendizaje*, de los automensajes que definen el *estilo de autorregulación de la emoción y la motivación centrado en el aprendizaje*, y del *esfuerzo*. Además, estas dos últimas variables dependen de la *autoeficacia* que, a su vez, incide en el *esfuerzo*. El rendimiento ha dependido positivamente del *esfuerzo* y, negativamente, del uso de las *estrategias de aprendizaje profundo*. Esta relación negativa puede deberse a cómo se evalúa el rendimiento académico.

Introduction

The use of learning strategies, which are usually framed within self-regulated learning (SRL) models (Panadero, 2017), has shown to influence positively educational achievement (Richardson et al., 2012; Schneider & Preckel, 2017). To design interventions to enhance SRL we must have reliable tools to measure the use of learning strategies; and precisely measuring SRL is complicated as it is an internal process (e.g. Boekaerts & Corno, 2005). One of the most contested methods to measure the use of learning strategies is self-report via questionnaires (Samuelstuen & Bråten, 2007). Yet it is still widely used to measure SRL as it has a number of advantages such as ease of application, interpretation, and reaching large sample size (Roth et al., 2016). Therefore, it is important that we continue developing solid self-report questionnaires. That is our aim here to inform about the validation of a new self-report tool that has some interesting innovative features.

Self-regulated learning and its measurement with self-report

The most popular definition states that "self-regulation refers to self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals" (Zimmerman, 2000, p. 14). Self-regulated learning theory provides a powerful and wide umbrella under which to study the more "traditional" learning strategies which are cognitive, metacognitive and behavioral, while incorporating strategies that regulate motivation and emotion (Panadero, 2017). Although there are different psychological traditions exploring SRL (Pintrich, 2000; Zimmerman, 2000) and even different traditions in the measurement of SRL (Panadero et al., 2016), SRL has been one of the main theoretical frameworks for at least the last two decades of research in educational psychology (Panadero, 2017).

Measuring SRL is complex and there has been a large portion of literature addressing this issue over the years (Boekaerts & Corno, 2005; Winne, 2020). According to Panadero et al. (2016) there has been three "waves" in SLR measurement: the first wave characterized by the massive use of self-report; the second wave characterized by irruption of online measurement (e.g. thinking aloud protocols, trace data or observations of overt behavior); and the third wave characterized by the combination of measurement and intervention. Interestingly, though self-report is the oldest method it offers access to psychological process no other method does (Pekrun, 2020). For that reason, among others, self-report via questionnaire is probably the most used technique still even if we have reached the third wave of SRL measurement.

The use of questionnaires presents a number of advantages such as being easy to administer, easy to obtain large samples, easy and efficient interpretation of results, high reliability if well-constructed, provide data that can be used for strong inferential statistical methods, etc. (e.g. Boekaerts & Corno, 2005; Fryer & Dinsmore, 2020; Roth et al., 2016). However, they also present

a number of disadvantages such as being decontextualized from the specific context where SRL strategies are deployed, inadequate grain size, results depend on the participants' introspective ability and honesty, etc. (Samuelstuen & Bråten, 2007). Basically, like any other research method, questionnaires also have flaws but, probably because of their popularity, they have received fierce criticism (Veenman, 2011).

Currently, there are plenty of validated SRL instruments such as the *Motivated Strategies for Learning Questionnaire* (MSLQ) (Pintrich et al., 1991) which is the most used SRL questionnaire (Broadbent & Poon, 2015; Roth et al., 2016); the *Learning and Study Strategies Inventory* (LASSI) (Weinstein et al., 1987); or the *Meta-cognitive Awareness Inventory* (MAI) (Schraw & Dennison, 1994). They all share some common features that can be found in other self-report tools (Roth et al., 2016). Namely, first, they are constructed from models of how self-regulation is deployed in an ideal regulation of performance; and second, a tendency to measure general capabilities instead of situational. Because of these two aspects, there have been critiques that self-regulatory inventories are based on ideal models of regulation, somehow disconnected from students' factual strategies (Schellings, 2011; Veenman, 2011) and that there is a problem with the granularity of the existing SRL questionnaires (Alonso-Tapia et al., 2014; Samuelstuen & Bråten, 2007). There are a number of reasons for the mismatch between the available questionnaires and students' regulatory actions such as: students are not able to label the strategies correctly (García-Pérez et al., 2020), they are not aware of some of the processes because they have become automatized or happen within microseconds (Panadero et al., 2016; Zimmerman, 2000), and most importantly, the traditional questionnaires do not reflect the actual range of strategies that students might use in daily basis (Coertjens et al., 2017; García-Pérez et al., 2020). Therefore, we identified a need for developing a questionnaire that measure students' action while studying in more realistic situations, closer to tasks they have to perform in a regular basis which also solves the problem of granularity.

The conceptualization of the Deep Learning Strategies Questionnaire

For that reason, our aim with the design of a new questionnaire is capturing realistic scenarios and their corresponding strategies that are commonplace for Secondary and university students. Based on our previous research in the creation of learning strategies questionnaires (e.g. Alonso-Tapia et al., 2014) and the exploration of real use of learning strategies (García-Pérez et al., 2020), plus our knowledge of the theoretical SRL models (Panadero, 2017) we identified four areas that the questionnaire needed to address. Next, we explain them in more detail:

(1) Basic learning self-regulation strategies: Most models divide the regulatory process in three cyclical phases: *preparatory* including task analysis and planning among others, *performance* where the task is executed while monitoring progress, and *appraisal* in which students evaluate their results (Panadero, 2017). In each

of these, more specific regulatory subprocesses take place. However, some of these subprocesses are complicated to reflect upon by the students because they are more automatic. For example, in the preparatory phase a number of motivational subprocesses (e.g. goal orientation, interest, etc.) take place in microseconds and students are not always aware and do not further elaborate on them (Zimmerman & Moylan, 2009). Therefore, we choose to stick with explicit strategies that are salient for each of the three main phases. These strategies are global and explicit and students have a clear understanding of them. Importantly, we decided to not explore the specific subprocesses because students are usually not aware of such level of strategizing (e.g. García-Pérez et al., 2020) and therefore this affects the validity and reliability of the questionnaires. In sum the items in this scale refer to actions related to general planning of the task, monitoring progress during performance and self-evaluating the results.

(2) Visual elaboration and summarizing strategies: As we know from cognitive psychology, students have to process, understand and store information in their memory for learning to actually occur (Kirschner et al., 2006; Soderstrom & Bjork, 2015). Our students know this reality quite well as they face it every time they are assessed; for example, unless they have knowledge to answer the questions in an exam, they will not pass it no matter how motivated they are. Because of this, students usually activate visual strategies (e.g. conceptual maps, tables) and summarizing strategies (e.g. creating bullet points, summaries) to organize the information into more important bits for more efficient processing. Research shows that the use of conceptual maps increases knowledge retention (Holley & Dansereau, 1984; Nesbit & Adesope, 2006) as the use of summarizing techniques has shown to have a relationship with SRL skills (Zimmerman et al., 1996). Research shows that these types of strategies are quite usual among our students (García-Pérez et al., 2020), thus the relevance of including a scale to evaluate its occurrence in our questionnaire.

(3) Deep information processing strategies: According to cognitive theory, both the association of new information to already existing one and the restructuring of existing information are crucial processes for successful acquisition of knowledge (Pozo, 1989; Soderstrom & Bjork, 2015). There are learning strategies that activate these types of processes (e.g. Aizpurua et al., 2018). Some examples are when students relate new material to knowledge they already have, when they try to apply what they are learning to real situations, or when they think about different alternatives to academic problems. Though these activities are usually cognitively demanding they benefit the students significantly. Therefore, we included a scale exploring learning strategies that are commonplace in classrooms around the world and have a direct connection to these deep processes.

(4) Social learning self-regulation strategies: This scale reflects two realities. First, learning does not happen in isolation but rather in social contexts that influence regulation. Processes such as co-regulation and socially shared regulation take place in classroom multiple times each day performed by teachers and peers who help the learner (Allal, 2020). Second, group work has become commonplace in classrooms because students have to become able to collaborate with others in a competent way in ever changing and more complex scenarios. Importantly, the social interaction does not always produce positive learning effects (e.g. free rider, status differential) as shown by the classic work by Salomon and Globerson (1989). Here we want to explore positive strategies such as asking for guidance or feedback to the teacher or peers, strategies that are positive for learning (e.g. Pintrich, 2000; Zimmerman, 2000). To our knowledge, these types of social aspects of regulation are not explored in such level of detail in existing questionnaires; thus, we included a scale to explore them.

Aim, research goals and hypothesis

Our aim is to create and validate a self-regulation questionnaire anchored to realistic students' use of learning strategies. Our research goals (RG) and hypothesis are:

RG1: Exploring the internal validity of the proposed model. We hypothesize that the four scales, because of their content and effects on learning, will correlate positively among them. Also, they will depend on a general construct, *Deep learning strategies,* evaluating the general tendency to use the strategies.

RG2: Exploring the external validity of the model against crucial factors influencing learning. We hypothesize four relationships. (1) A positive relationship with *effort* and *self-efficacy*, two variables that have a strong predictive power over academic performance (Richardson et al., 2012); (2) Regarding goal orientations, a positive relationship with *learning goals* and a negative one with *performance goals* and, especially, *avoidance goals*. It is important to explore this relationship because they might moderate the different approaches to learning and regulatory strategies (Pintrich, 2000); (3) A positive relationship with the *Learning self-regulatory style* of emotion and motivation (Alonso-Tapia et al., 2014), this being a measurement of self-regulatory actions; and, (4) a positive predictive power of the deep learning strategies construct over performance. It has been well established learning and regulatory strategies have a positive yet moderate relationship to academic performance (Dignath et al., 2008; Richardson et al., 2012; Schneider & Preckel, 2017). However, as shown by Soderstrom and Bjork (2015), there is difference between learning and performance. Therefore, we should expect a similar type of relationship between our questionnaire construct and academic performance, but this prediction might fail not because of lack of quality of the scale developed for assessing the strategies, but because performance information may come from inadequate learning assessment instruments (Baird et al., 2017).

Method

Participants

A total of 601 higher education students from four different universities in Madrid participated in this study. Regarding their description 51.1% were women; the average age was 20.44 (*SD* = 3.96, range 17 - 53); 47.1% were freshmen, 35.1% sophomore, 17.8% junior; 43,6% were Psychology undergraduates, 47.4% Physical Activity and Sport undergraduates, and 8.8% from a combined programme on Psychology + Criminology. The sample was randomly divided in two subsamples to allow for cross-validation analyses.

Instruments

Deep Learning Strategies Questionnaire. This is the instrument to be validated in this study. In its final and depurated version (Appendix A), it contains 30 items to be answered in a 5-points Likert scale (Totally disagree – Totally agree). They were designed to represent the types of strategy corresponding to the four learning scenarios described above in which students aim for learning in a deep way: *learning self-regulation strategies* (8 items), *deep information processing strategies* (8 items), *visual elaboration and summarizing strategies* (8 items), and *social elaboration study strategies* (6 items).

Situated Goals Questionnaire (SGQ-U) (Alonso-Tapia et al., 2018). This questionnaire was used for assessing goal orientations as moderating variables. It contains 30 items grouped in six first order scales: *desire to learn*, *desire to be useful*, *desire to success*, *desire to*

pass, *desire to give up*, and *desire to avoid failure*. These scales are related to tree second order factors that measure goal orientations: *learning orientation* (α = .86), *performance orientation* (α = .87), and *avoidance orientation* (α = .83). The items are answered in a 5-points Likert scale (Totally disagree - Totally agree).

Effort regulation scale and *Self-efficacy for learning and performance scale* extracted from the *Motivated Strategies for Learning Questionnaire (MSLQ)*, (Pintrich et al., 1991). Both variables are answered in a 5-points Likert scale (Totally disagree – Totally agree). The *effort* scale contains 4 items (α = .69). The *self-efficacy* scale contains 8 items (α = .93).

Emotion and Motivation Self-regulation Questionnaire (EMSR-Q) (Alonso-Tapia et al., 2014). This questionnaire includes 20 items to be answered in a 5-points Likert scale (Totally disagree – Totally agree). They are structured around five first order scales: (1) *Avoidance oriented self-regulation*; (2) *Negative self-regulation of stress*; (3) *Performance oriented self-regulation*; (4) *Process oriented self-regulation*; and, (5) *Positive self-regulation of motivation*. At the same time these are grouped in two general scales, *Learning self-regulation style*, with 12 items and a reliability index Cronbach's α = .78, and *avoidance self-regulation style*, with 12 items and a reliability index α = .86. The first scale includes self-messages and actions that have positive effects on the students' learning goals. The highest the value in this scale, the more positive for learning are the emotional and motivational strategies the student is performing. The second scale includes self-messages and actions showing lack of regulation or orientated towards avoiding the task. The highest the value in this scale, the more negative and detrimental for learning are the emotional and motivational strategies the student is performing. In this study, only scores corresponding to the first self-regulatory style will be used.

Procedure

Participants were contacted during their classroom time. The sample was chosen for convenience reasons. One of the researchers informed the students about the study and the conditions of participation. In three of the universities the data collection occurred in the classroom itself with no gratification for the voluntary participation. In the fourth university, students went to a lecture hall outside their regular time and received credits for it. The overall time of application was 1 hour and 20 minutes. Approximately half of the participants filled out the informed consent, the questionnaires, and the self-reported grade mean-grade online and the other half, using paper and pencil. The sample was randomly divided in two sub-samples one to be used for the initial analysis and the second sample for cross validating the results. This study was approved by the Ethical Committee at the Universidad Autónoma de Madrid (Reference number CEI-84-1557) where the first author and PI of the project worked from at the time of the data collection.

Data analysis

In order to determine the *Deep Learning Strategies Questionnaire* factorial structure, we carried out several confirmatory factor analyses (CFA). First, we tested whether that all items depended on only one general factor (Model 1, CFA-1), a possibility that would invalidate our hypothesized model according to which the situations play an important role in the students' use of study strategies. Second, we used as base model a structure according to which each of the four group of strategies only correlated with the others (Model 2, CFA-2). Third, in order to cross-validate the model, we performed a confirmatory multiple group analysis using the two subsamples (Model 2, CFA3). Fourth, a second model was tested according to which, the factors corresponding to the four groups of strategies

depend on a general second order factor (Model 3, CFA-4). Fifth, in order to cross-validate this model, we performed also a confirmatory multiple group analysis using the two subsamples (Model 3, CFA-5). The reliability indexes of the scales were calculated using Cronbach's α coefficient and McDonald's ω, as well as composed reliability and average variance extracted.

As Likert scales are categorical ordered variables, estimates were obtained using the weighted least squares means and variance adjusted estimation method (WLSMV). Absolute fit indexes ($\chi^2, \chi^2/df$), incremental fit indexes (IFI) and non-centrality fit indexes (TLI, CFI and RMSEA) as well as criteria for acceptance or rejection based on the degree of adjustment described by Hair et al. (2010) ($\chi^2/df \leq 5$, TLI, CFI ≥ .90, RMSEA ≤ .08). Analyses were carried out using the program MPLUS v7 (Muthén & Muthén, 2012). Reliability indexes of the scales of the questionnaires used in the study were also estimated.

To evaluate the external validity of the *Deep Learning Strategies Questionnaire*, a path-analysis was carried out with the first subsample, and then was cross validated using the two subsamples. Self-estimated mean grade, as an index of performance, was used as criterion. *goal orientations* and *self-efficacy* were used as initial predictors, as they were supposed to affect most of the remaining variables. Then, *Effort* and *Learning self-regulatory style* were included in the model, as they were supposed to convey the effects of *goal orientations* and *self-efficacy*. *Deep learning strategies* were supposed to convey part of the effects of all the variables just quoted on performance.

Results

Three preliminary notes. First, the first order scale *Social elaboration study strategies* contained 8 items when it was initially conceived. However, a content analysis of the items after gathering the data, indicated that two of them did not address social aspects of learning; therefore, they were deleted, and all analyses were run with the remaining items. Second, to explore whether the correlation matrix was adequate for factor analysis, we calculated the KMO index (KMO = .900) and the Bartlett sphericity test (BST = 6267.55, *df* = 435, *p* < .0001). Third, a descriptive analysis of item statistics was realized. Results are shown in Table 1. In all items, the minimum and maximum values found were 1 and 5, and the 60% of values was between 3 and 4.

(RG1) Exploring the validity of the Deep learning strategies model

Model 1. CFA1. We present in Figure 1 the standardized estimates of the first confirmatory model as well as the squared multiple correlations. All estimated weights (λ) were significant (*p* < .001) (see Table 2). As for the fit statistics obtained for the proposed model, as can be seen in Table 2, chi-square was significant, but the ratio χ2 /*df*, the RMSEA, TLI and CFI adjustment indexes show that the model cannot be accepted. Therefore, no cross-validation analysis of this model was carried out.

Model 2. CFA2. We present in Figure 2 the standardized estimates of the second confirmatory model as well as the squared multiple correlations. All estimated weights (λ) were significant (*p* < .001) (see Table 2). As for the fit statistics obtained for the proposed model, as can be seen in Table 2, chi-square was significant, but the ratio χ^2/df, the RMSEA, TLI and CFI adjustment indexes were well inside the limits to accept the model.

Model 2. CFA3. Cross-validation. Using the other half of the sample, a cross-validation analysis was carried out. All weights (λ) were significant, but fit values were similar to those of CFA; actually, χ^2/df improved (see Table 2). Therefore, the model can be accepted.

Table 1

Descriptive statistics for each item of the *Deep Learning Strategies Questionnaire*

| Item	M	SD	Item	M	SD	Item	M	SD	Item	M	SD
BLRS1	4.05	0.76	VisEl1	3.91	1.19	DIPS1	3.64	0.86	SLSR1	3.58	1.07
BLRS2	3.86	0.60	VisEl2	2.61	1.46	DIPS2	3.96	0.73	SLSR2	3.03	1.50
BLRS3	3.81	0.87	VisEl3	2.33	1.71	DIPS3	4.09	0.69	SLSR3	3.15	1.20
BLRS4	3.87	0.66	VisEl4	2.62	1.70	DIPS4	3.72	0.81	SLSR4	3.68	1.14
BLRS5	3.74	0.85	VisEl5	3.39	1.30	DIPS5	3.72	0.83	SLSR5	3.52	1.09
BLRS6	3.95	0.61	VisEl6	2.56	1.57	DIPS6	3.86	0.67	SLSR6	3.42	0.99
BLRS7	3.75	0.67	VisEl7	3.88	1.16	DIPS7	3.83	0.72			
BLRS8	3.91	0.68	VisEl8	3.80	1.23	DIPS8	3.96	0.70			
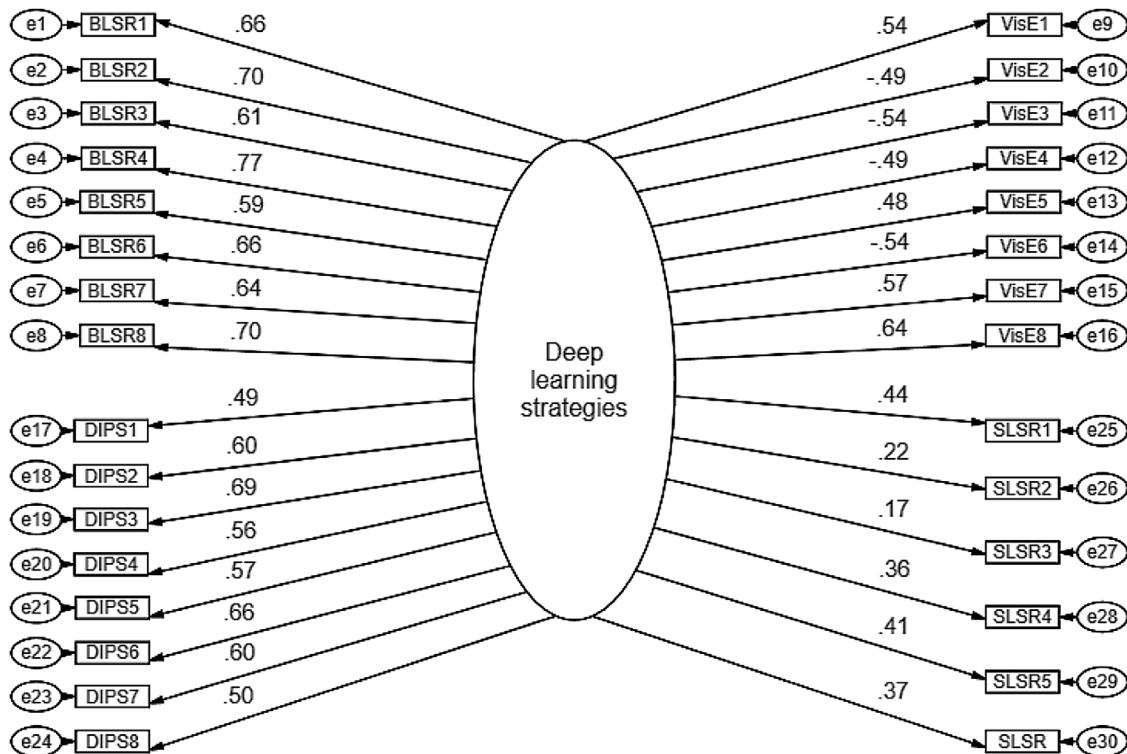
Figure 1. DLS-Q. Model 1: Mono-factor. Standardized regression weights

Table 2

Goodness of fit statistics for each baseline model tested and for multi-group cross-validation analysis

Analysis	χ^2	df	p	χ^2/df	TLI	CFI	RMSEA
Model 1 – Mono-factor CFA-1 ($n = 301$)	2204.48	405	<.0001	5.44	.71	.73	.121
Model 2 – Correlated factors CFA-2 ($n = 301$)	966.46	399	<.0001	2.42	.91	.92	.069
Model 2 – Cross validation CFA-3 ($n_1 = 301$; $n_2 = 300$)	2282.49	1036	<.0001	2.20	.91	.91	.063
Model 3 – Hierarchical CFA-4 ($n = 301$)	948.88	401	<.0001	2.36	.91	.92	.067
Model 3 – Cross validation CFA-5 ($n_1 = 301$; $n_2 = 300$)	2254.03	1040	<.0001	2.16	.92	.91	.062

Model 3. CFA4. The aim of this analysis was to test whether the four first order factors corresponding to the four groups of strategies were indicators of a general construct named *Deep learning strategies.* Figure 3 shows such model. As can be seen in Table 2, this model shows a goodness of fit similar to that of Model 2, though slightly higher according to some fit indexes. Chi-square was significant, but the ratio χ^2/df, the RMSEA, TLI and CFI adjustment indexes were well inside the limits that allowed the model to be accepted.

Model 3, CFA5. Cross-validation. Using the other half of the sample, a cross-validation analysis was carried out to further test Model 3. In this analysis, all weights (λ) were significant. Fit values were similar to those of CFA-3 and χ^2/df actually improved showing the best goodness of fit of the four CFA (see Table 2). Therefore, Model 3 had the best fit and it was chosen to check its external validity.

Reliability

Reliability Cronbach α and McDonald ω indexes of the *Deep learning strategies questionnaire* scales and of the remaining questionnaires used in the study, as well as the Average Variance Extracted and the composed reliability are shown in Table 3. As it can be seen, most of them are quite good (values >.80 in most scales).

(RG2) Exploring the external validity of deep learning strategies model

Figure 4 shows the path analysis and Table 4 the fit indexes of the model including the data from the validated questionnaire - *Deep learning strategies-*, goal orientations, *learning self-regulation*
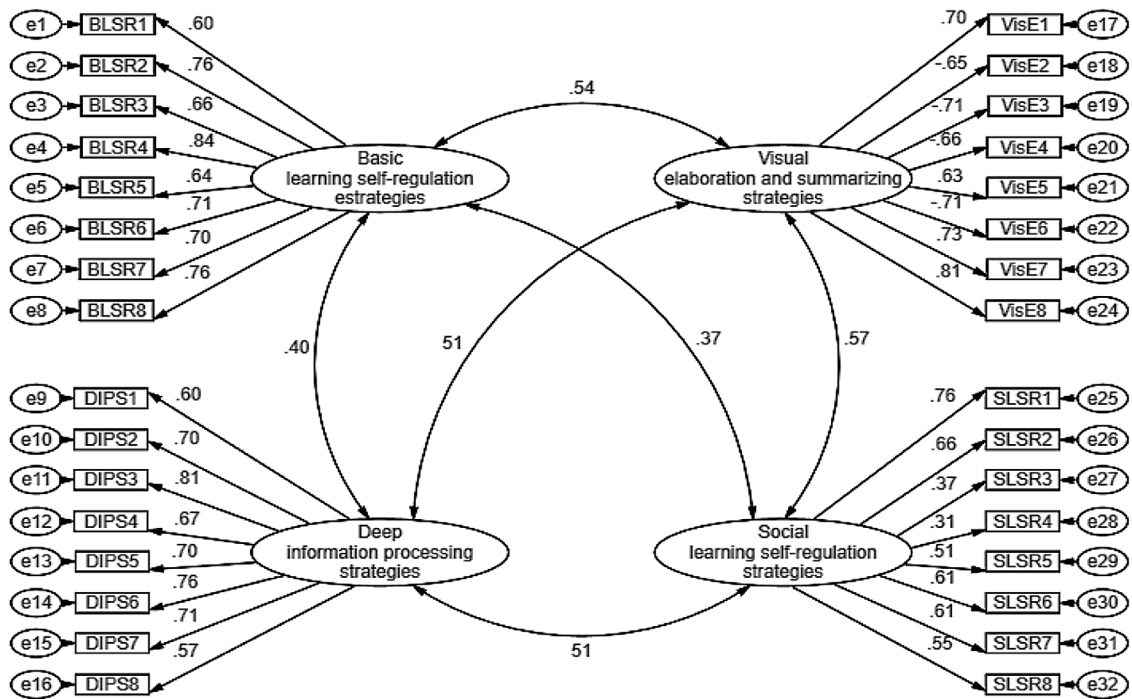
Figure 2. DLS-Q. Model 2: Correlated factors. Standardized regression weights, and correlations between factors.
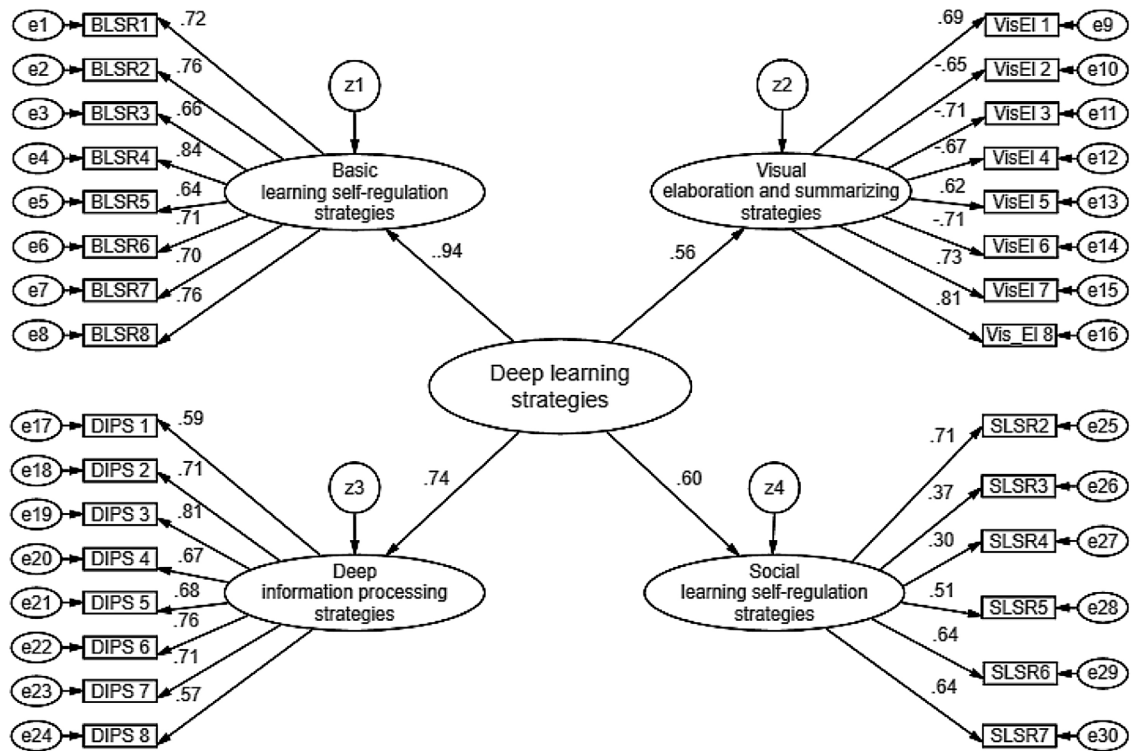

Figure 3. DLS-Q Model 3: Hierarchical. Standardized regression weights, and correlations between latent factors

style, self-efficacy, effort, over the *reported mean grade*. In general, results are aligned with hypothesis except for the unexpected relationships of *Avoidance goal orientation*, as we will explain in the discussion.

Initial path analysis. In this analysis, as shown in Table 3, all weights (λ) are significant ($p < .001$). Fit indexes showed that the statistic χ^2 is significant probably due to sample size, and that the remaining indexes fell short of the standard limits of significance,

except the ratio χ^2/df (3.31 < 5) and RMSA (.08 = .08). Therefore, a cross validation analysis was performed.

Cross-validation path-analysis. In this analysis, all weights (λ) are significant ($p < .001$). Again, fit indexes showed that the statistic χ^2 is significant probably due to sample size, and that IFI and CFI indexes fall short of the standard limits of significance. However, the ratio χ^2/df (3.04 < 5) and the RMSEA index (.05 < .08) are acceptable. Besides, results of group comparison showed that

Table 3

Reliability indexes of the *Deep learning strategies questionnaire* scales and of the remaining questionnaires used in the study

| First order scales & general second order scale	Average variance extracted	Composed reliability	Cronbach α	McDonald ω
General: Deep learning strategies	52.42	.81	.86	.81
Basic learning self-regulation strategies	54.02	.91	.85	.91
Visual elaboration and summarizing strategies	49.13	.89	.84	.89
Deep information processing strategies	47.65	.88	.85	.88
Social learning self-regulation strategies	30.00	.85	.64	.85
Avoidance Self-regulation style	56.50	.81	.81	.81
Learning Self-regulation style	69.20	.86	.77	.86
Self-efficacy	86.30	.93	.87	.93
Effort	31.00	.64	.64	.64
Learning Orientation	77.30	.87	.85	.87
Performance Orientation	86.50	.93	.83	.93
Avoidance Orientation	45.10	.80	.78	.80
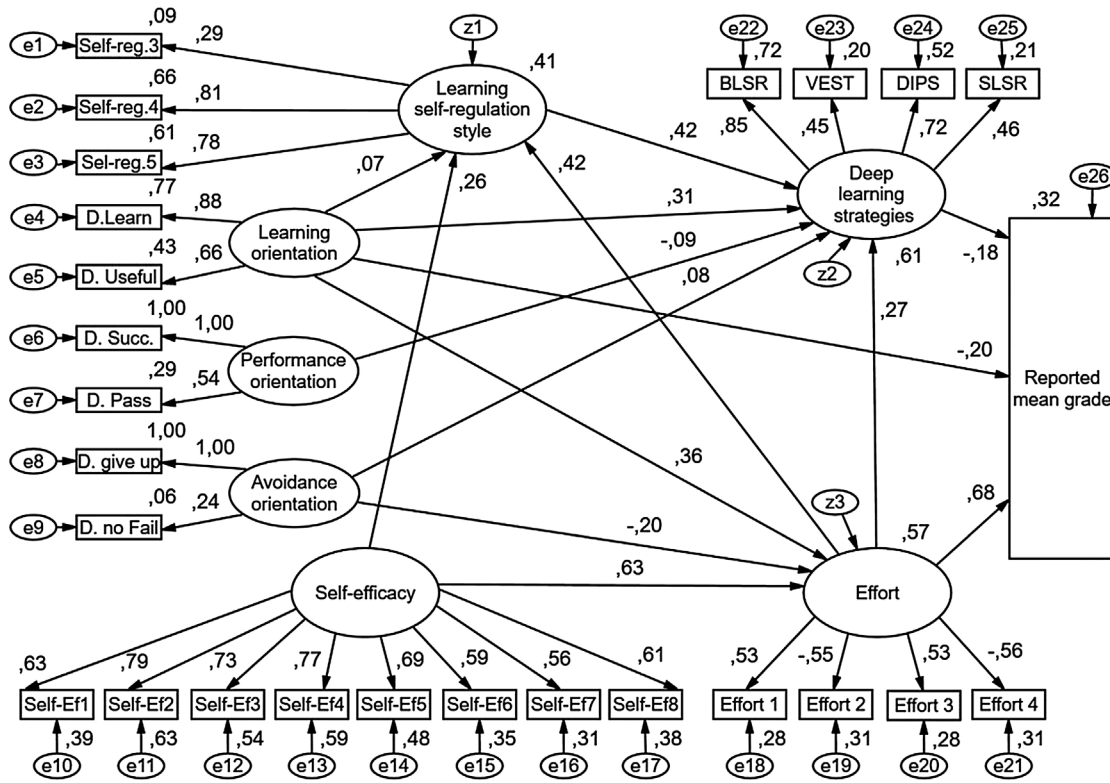
Figure 4. Path analysis: measurement weights, regression coefficients, and explained variance of dependent variables.

fit does not decrease if restrictions of equality between parameters are imposed for measurement weights (χ^2 = 24.57, p = .27), measurement intercepts (χ^2 = 51.49, p = .30), structural weights (χ^2 = 65.84, p = .22), structural covariances (χ^2 = 69.53, p = .24) and structural residuals (χ^2 = 71.70, p = .27). Therefore, the model is well estimated.

Direct and indirect effects. Table 5 shows the mediator variables and criterion explained variance. *Effort* depends (57%) on *self-efficacy* and *learning orientation*. *Learning self-regulatory style* depends (41%) on *self-efficacy*, *learning orientation* and *effort*; but the effect of the two first variables is indirectly mediated through *effort* (see Figure 3). Once the effects of *self-efficacy* and *learning orientation* are taken away *effort* explains a 0% of *learning self-regulation style*. *Deep learning strategies* depend (61%) mainly on *self-efficacy*, *avoidance orientation*, *learning orientation*, *effort* and *learning self-regulatory style*. However, the effects of *self-efficacy* and *learning orientation* are mediated through *effort* and *learning self-regulatory style*, a variable that also mediates the effect of *effort*. Finally, variance of *reported mean grade* (32%) is explained mainly by *effort* that

conveys in part the effect of *learning orientation*, *self-efficacy*, *learning self-regulatory style* and *avoidance orientation* (53%). *Effort*, then, explains the 15% of *reported mean gr*ade.

Discussion

Our aim was to create and validate a self-regulation questionnaire anchored to realistic students' use of learning strategies through two research goals (RG). To develop this type of questionnaire is necessary because existing tools are usually created from theoretical SRL models that miss some of the most usual learning strategies students use (Schellings, 2011; Veenman, 2011). Therefore, the need for more realistic SRL measurement tools.

The RG1 was to check the internal validity by comparing three models and performing cross-validation analyses with two subsamples. As the first model presented a bad fit, it was not cross-validated. As for Models 2 and 3, it was found that, while both models had an adequate goodness of fit, our preferred theoretical model -in which the four first order scales contribute to a general

Table 4
Path analysis: Goodness of fit statistics for group-1 and for multi-group cross-validation analysis

Analysis	χ^2	df	p	χ^2/df	TLI	CFI	RMSEA
Path for Group 1 ($n = 301$)	954.65	288	<.0001	3.31	.70	.76	.08
Cross validation ($n_1 = 301$; $n_2 = 300$)	1952,43	641	<.0001	3.04	.75	.78	.05

Table 5
Path analysis. Variance explained of mediators and final variables, and total, direct and indirect effects

Mediators and criterion	Effort	Learning self-regulatory style			Deep learning strategies			Reported mean grade		
Variance explained	57%		41%			61%			32%	
Predictors/Effects	Total	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect
Self-efficacy	.634	.528	.259	.269	.395		. 395	.362		.362
Avoidance orientation	-.196	-.083	-	-.083	.011	.077	-.089	-.132		-.132
Learning orientation	.357	.218	.067	.151	.500	.312	.312	-.051	-.203	.152
Effort		.424	.424		.451	.273	. 178	.601	.684	-.082
Learning SR style					.419	.419		-.077		.077
Performance orientation								.016		.016
Deep learning strategies								-.183	-.183	

construct- had better fit. Therefore, the final model is structured around a general factor named *deep learning strategies*. The four first order scales contribute to the general factor and present adequate reliability. Therefore, the higher the value in the *deep learning strategies* the more the students regulate their learning strategies and achieve a deeper processing of new information, which is directly related to more learning (e.g. Richardson et al., 2012).

Our RG2 was to find empirical evidence about factors that might influence the use of *deep learning strategies* and the effects of such use in performance –i.e. *reported mean grade*. As shown in the path analysis model, the use of *deep learning strategies* is affected by the three types of *goal orientation* (*learning, performance* and *avoidance*), and by *learning self-regulation style* and *effort*. All correlations were in the expected direction except *avoidance orientation*, which was positive though it represents only a 1.7% of variance. As we know from previous research, students have always features of the three types of goal orientation though in different degree (Hofverberg & Winberg, 2020). *Avoidance orientation* is activated when students focus on the negative consequences following a potential failure. In this case, students might activate deep learning strategies to increase the possibilities of avoiding failure, ergo the positive correlation. *Self-efficacy* also affects the use of *deep learning strategies*, but its effect is indirect, through *effort* and *learning self-regulation*. The higher *self-efficacy*, *effort* and *learning self-regulation style*, the higher the use of *Deep learning strategies*. These results could be expected according to the nature of variables implied and previous evidence (Cerezo et al., 2019; Dignath et al., 2008).

As for the effect of *deep learning strategies* on *reported mean grade*, the result was opposite to our hypothesis. There is a key aspect here: we hypothesized a positive correlation to mean grade because we considered it an index of learning, and precisely the new questionnaire measures strategies that enhance deep learning. However, the mean grade average depends on how classroom assessment is designed, and performance and learning are not the same (Baird et al., 2017). In fact, *performance* is often an unreliable index of whether the relatively long-term changes that constitute learning have taken place: learning can occur even when no discernible changes in performance are observed, and the converse has also been shown, that is, improvements in performance can fail to yield significant learning (Soderstrom & Bjork, 2015). According to these authors, research suggests that "fleeting gains during acquisition are likely to fool instructors and students into thinking that permanent learning has taken place, creating powerful illusions of competence", while "conditions that appear to degrade acquisition performance are often the very conditions that yield the most durable and flexible learning". (p. 193). Therefore, the

negative correlation between the use of *deep learning strategies* and *reported mean grade* might make sense if assessment practices reinforce the use of strategies aimed at assuring "short-term learning" as it has been shown to happen frequently (Panadero et al., 2019), which creates illusions of competence instead of deep learning. This hypothesis is further supported by the also negative correlation between *learning orientation* and *reported mean grade*, showing that having learning goals does not guarantee obtaining higher grades in our sample as research has found previously (Zhou & Wang, 2019).

Our questionnaire presents more practical and every day-use strategies that some of the main tools in the field, which are based on more general educational experiences and built with an ideal self-regulatory behavior (e.g. Pintrich et al., 1991; Schraw & Dennison, 1994; Weinstein & Palmer, 2002). Unfortunately, we know that students usually do not self-regulate in such advanced ways as the theoretical SRL models propose. We suggest that our questionnaire can be used as a stand-alone measurement if the researchers want to measure realistic strategies; or in combination with other SRL questionnaires as to obtain a more accurate picture of, both, the ideal and the realistic regulatory actions. Future research should explore in more details the relationship of the new tool to existing SRL ones (e.g. Jiménez et al.,2018), as we only explored one here (i.e. EMSR-Q). Additionally, it would be interesting to investigate if the internal structure of the model can be translated to other educational levels. To overcome an important limitation of the present study, it would be important to calculate the predictive power of the new questionnaire scores over real grade point average, in contrast to the self-reported mean grade that was used here. Another limitation has to do with the fact that the AVE value of three of the scales fell short of the standard limits usually accepted. A final limitation is that we did not control for differences between the three universities in which there was no compensation for participation against the one in which participants received credits. In any case, that university had the smallest proportion of participants.

While self-report, and even more precisely, questionnaires and inventories have received a significant number of critique when used to measure SRL, they are still used very often as they also have a significant number of advantages. Even if plenty of SRL questionnaires already exist, we identified that there was need for a new one that would (a) not be distilled directly from a general theoretical model of self-regulated learning, and (b) would be close to more realistic strategies that students use in daily basis. From those premises, we proposed a model and created the *Deep learning strategies questionnaire* from that foundation. This study shows its internal and external validity. The four scales reflect a variety

of deep learning strategies related to different demands due to differences in content and learning situations: *basic learning self-regulation strategies*, *visual elaboration and summarizing strategies*, *deep information processing strategies*, and *social elaboration study strategies*. Our belief is that the new instrument will contribute to the SRL literature as a measurement tool as it contains unique features.

Funding

Appendix A.

Deep Learning Strategies questionnaire DLS-Q

We are trying to understand what goes through the minds of learners while they study. Our purpose is to determine what instructional scaffolds we shall offer to students to facilitate their learning. Therefore, we ask you to point out **to what degree thoughts like the ones below cross your mind when you are performing academic assignments**. Using the following scale:

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

1	I analyze in depth the task I have to complete so that it is clear to me what I have to do (S1)	1 2 3 4 5
2	I often make diagrams or drawings to represent what I study (S2)	1 2 3 4 5
3	When I read or hear an idea or a conclusion in class, I think of possible alternatives (S3)	1 2 3 4 5
4	When I figure out what I have to do, I try to visualize it and follow through (S1)	1 2 3 4 5
5	I do not usually organize information that I study in tables because it does not help me to learn (S2): Negative item	1 2 3 4 5
6	I relate what I am learning in class to my own ideas (S3)	1 2 3 4 5
7	I often discuss with my classmates ideas or aspects of what I have been studying (S4)	1 2 3 4 5
8	While I perform a task, I check if the steps I am taking are appropriate (S1)	1 2 3 4 5
9	Unless the teacher asks me, I do not usually summarize the texts I study (S2): Negative item	1 2 3 4 5
10	When I study, I relate the material I read to what I already know (S3)	1 2 3 4 5
11	I usually participate in class discussions, asking questions or making comments to the teacher (S4)	1 2 3 4 5
12	If the teacher gives me a tool to self-assess I would use it (S1)	1 2 3 4 5
13	When I study for an assessment task (e.g. exam) I write short summaries with the main ideas and concepts of readings (S2)	1 2 3 4 5
14	I relate ideas from the class with other ideas whenever possible (S3)	1 2 3 4 5
15	I ask the opinion of my classmates on how I am doing on a task (S4)	1 2 3 4 5
16	When I am working on a task I stop to check if I am progressing as planned (S1)	1 2 3 4 5
17	I usually study using different strategies (memorize, make diagrams, etc.) depending on the subject in question (S2)	1 2 3 4 5
18	When studying, I often mentally relate the content I am working on to other subjects (S3)	1 2 3 4 5
19	If the teachers provide us with presentations, I take notes in them because it makes everything clearer (S4)	1 2 3 4 5
20	At the end of a task I review what I have done to evaluate if I did it correctly (S1)	1 2 3 4 5
21	I do not usually make concept maps to relate the concepts I study because they are of little use (S2): Negative item	1 2 3 4 5
22	When studying, I look for possible relations between what I study and the situations to which it could be applied (S3)	1 2 3 4 5
23	If I do not do a good job on a task or an exam, I ask the teacher to give me more information about how to improve (S4)	1 2 3 4 5
24	Before I start working on a task, I carefully plan what to do (S1)	1 2 3 4 5
25	I do not usually make graphs or diagrams while studying or solving problems because they do not help me learn (S2): Negative item	1 2 3 4 5
26	I look for situations to apply course content (S3)	1 2 3 4 5
27	Whenever I can, I try to discuss with my classmates ideas or aspects of what I have been studying to learn more (S4)	1 2 3 4 5
28	I read instructions for the assignments and exams as many times as necessary to understand what is required (S1)	1 2 3 4 5
29	If possible, I create tables to organize the information contained in texts and assignments (S2)	1 2 3 4 5
30	I usually study trying to visualize the task context (S3)	1 2 3 4 5

S1 = Basic learning self-regulation strategies; S2 = Visual elaboration and summarizing strategies; S3 = Deep information processing strategies; S4 = Social learning self-regulation strategies.

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