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Self-Regulation Profiles and Learning Preferences: A Study of Spanish University Students

I. Muñoz-San Roque[1] | G. Aza-Blanc[2] | M. Hernández-Arriaza[1] | E. Fernández[3] | J. R. Martínez-Fernández[4]

[1]Department of Education, Comillas Pontifical University, Madrid, Spain | [2]Department of Psychology, Comillas Pontifical University, Madrid, Spain | [3]School of Applied Social Studies, University College of Cork, Cork, Ireland | [4]Facultad de Psicología, Universitat Autònoma de Barcelona, Bellaterra, Spain

Correspondence: I. Muñoz-San Roque (isabelmsanroque@comillas.edu)

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ABSTRACT

Self-regulation of learning is a crucial factor in how students learn and manage their own emotional, cognitive and metacognitive resources. This study has three main goals: first, to identify self-regulation of learning profiles among 697 Spanish university students using cluster analysis, second, to differentiate these profiles based on sex, academic year, and field of study (Education, Humanities and Social Sciences, Economics and Engineering); and finally, to uncover their preferred ways of learning, teaching methodologies, and assessment methods. Our study has revealed four types of learners: strategic (28.12%), non-strategic (26.11%), external (22.81%) and anxious (22.96%). Findings revealed that strategic learners, characterised by the highest levels of self-regulation and self-efficacy, preferred active and applied methodologies, whereas anxious learners exhibited the highest levels of study-related exhaustion ($p < 0.001$). Our study highlights the importance of recognising the diversity of self-regulated learning profiles among university students to tailor teaching, learning, and assessment strategies, that improve academic performance across a broader range of learners. To support less effective learner profiles, it is essential to provide additional scaffolding through personalised tutorials, enhance planning skills, and deliver structured feedback. Additionally, diversifying teaching and assessment methods—such as incorporating video-based resources for anxious learners and offering practical, step-by-step guidance—can help these students gradually develop autonomy and improve self-regulation.

1 | Introduction

In recent times, we have seen an increasing interest in teaching and learning in tertiary level educational institutions. This growing interest has been accompanied by the introduction of a wider and more diverse set of teaching activities, and assessment methodologies. Learning patterns, understood as a coherent set of learning activities used by students, which also include motivation and beliefs (Shum et al. 2024; Vermunt and Donche 2017), have opened up important research avenues for tertiary education.

Vermunt and Vermetten (2004) distinguish a number of learning patterns based on the combination of four main components or dimensions: learning approaches, motivational orientation, self-regulation strategies and cognitive processes. Among these components, learning regulation appears as the key component reconciling beliefs and all those processes that students use to control and guide their own learning. These self-regulation processes are essential to determine how students approach learning tasks and manage their cognitive and metacognitive resources to reach their goals (García and Pintrich 1994; Hadwin et al. 2017; Hattie and Timperley 2007; Panadero 2017; Zimmerman and Martinez-Pons 1990; Zimmerman and Moylan 2009).

Drawing on the model initially proposed by Vermunt (1998), Martínez-Fernández and Vermunt (2015), Martínez-Fernández (2018), and Martínez-Fernández et al. (2024) highlight the need to identify types of self-regulatory learning strategies among students. The first type of strategy they identify is associated with high levels of self-regulation: here, the student is able to regulate their own learning process autonomously, both in relation to academic content as well as the learning process itself. The second strategy is characterised by external regulation, that is, the student is heavily guided by the resources and guidelines provided by teachers. Regarding the third and final strategy, students report perceiving difficulty in applying self-regulatory learning strategies in certain contexts.

Paying attention to learning regulation is important for several reasons. Firstly, learning regulation appears to be closely linked to the quality of learning, since students who are able to self-regulate themselves adopt the most effective strategies to manage different learning tasks. These students are able to establish clear goals, monitor their own progress, select the most effective learning strategies and evaluate their own learning (Zimmerman 2002, 2008, 2011). Moreover, self-regulation of learning can also influence students' flexibility and ability to respond to specific tasks and different learning contexts. In summary, students who are able to self-regulate their own learning processes are more able to adjust their learning strategies to changing demands, different types of tasks, and diverse sets of learning contexts and assessments (Bardach et al. 2023; Mertens et al. 2024; Pintrich 2000).

While some studies highlight significant differences in the use of cognitive strategies, defined as mental techniques that learners apply to process, store, and retrieve information, including rehearsal, elaboration, and organisational strategies, between men and women (Agha and Rehman 2016; Wolters and Pintrich 1998), others do not find conclusive relationships (Liu et al. 2021; Malik and Parveen 2019; Zimmerman and Martinez-Pons 1990). Similarly, some longitudinal studies, such as those by Räisänen et al. (2020), Räisanen et al. (2021), report no notable differences by grade level.

Additionally, some research suggests that students in fields such as Education, Humanities, and Social Sciences tend to exhibit less strategic and more anxious learning profiles, highlighting the need for targeted pedagogical interventions. These interventions should aim to foster self-regulation through a combination of participatory, experiential, and digitally supported strategies—that is, instructional approaches that actively engage students through dialogue, collaboration, reflection, and applied tasks. Examples include peer instruction, cooperative learning, role-playing, and problem-based learning, all of which have been shown to promote metacognitive awareness, learner autonomy, and motivational engagement (Fernández-Ruiz et al. 2021; Melchor Gutiérrez and Tomás 2018; Panadero et al. 2022). Self-regulation is also linked to the concept of self-efficacy, defined by Bandura (1997) as the self-belief in one's own capacity to carry out tasks and fulfil objectives. These processes influence significantly students' motivation and persistence levels. Students with higher levels of self-efficacy tend to achieve greater academic success (Pajares 2008) and adopt more effective self-regulatory learning strategies, such as setting up clear goals and monitoring their own progress (Efklides 2014; Pintrich 2000; Schunk and Pajares 2002).

Research also highlights how emotional and cognitive regulation play a key role in how students manage academic stress or study-related exhaustion. Cognitive self-regulation refers to the ability to control one's own thinking and learning processes—for example, by focusing attention, applying strategies, or monitoring comprehension—while emotional self-regulation involves recognising and managing emotions that can hinder or enhance learning, such as frustration, anxiety, or motivation (Boekaerts 1996; Pintrich 2000). Students with high levels of both cognitive and emotional self-regulation are better equipped to adopt strategies that reduce study-related exhaustion (Seibert et al. 2017; Vega-Martínez et al. 2023) and enhance academic performance, which, in turn, contributes to lower anxiety levels (González et al. 2017). These trends illustrate the close relationship among self-efficacy, learning strategies, and emotional self-regulation.

Drawing on these points, we can argue that university teaching should seek to activate coherent methodologies that boost students' self-regulation of learning. A number of studies have shown that there are several teaching methodologies that allow students to become more autonomous in the management of their own learning (De la Fuente et al. 2022; Hattie 2011; Kirschner et al. 2006; Kolb 2014; Oakley 2014; Panadero 2017, 2023; Sternberg 2003). For example, Hattie (2011) highlights the value of teaching students metacognitive abilities, such as planning, monitoring and evaluating their own learning; Kolb (2014) and Sternberg (2003) highlight how methodologies that promote direct experiences and critical reflection can improve learning patterns; and studies such as Fernández-Ruiz et al. (2021), Panadero et al. (2022) and Panadero (2023) also emphasise the role of self-assessment and peer-assessment in boosting more effective and self-regulatory learning processes among students.

Finally, there are also studies that point to the need to contextualise these debates about teaching and learning at tertiary level within an increasingly digital context. According to some authors, teaching methods should seek to respond to the specific needs of a digital age, including: the use of technological resources more associated with visual and interactive learning methods (such as simulations, gamification, case studies and so on); the promotion of collaborative spaces (research projects); and the use of more practical and self-managed ways of learning (Fodor and Jaeckel 2018; Greenwood 2011; Puiu 2017; Seemiller and Grace 2017). These approaches advocate for teaching methodologies that not only motivate students, but also seek to equip them with essential skills for professional success (an example can be found in the work of Szabó et al. 2021).

Recent literature has emphasised the pedagogical value of diverse instructional approaches that promote self-regulated learning. Studies have shown that active and experiential methods, such as *problem-based learning* and *case-based approaches*, foster metacognitive engagement and deeper learning processes (Fernández-Ruiz et al. 2021; Panadero et al. 2022). Likewise, collaborative and participatory strategies, including peer instruction and group projects, are associated with increased motivation, co-regulation, and academic persistence (Hadwin et al. 2017; Melchor Gutiérrez and Tomás 2018). In parallel, digitally enhanced methods—such as gamification, flipped classrooms, and video-based content—have gained relevance in response to the changing demands of Generation Z learners and the post-pandemic shift to hybrid environments (Evans et al. 2019; Murphy 2021; Szabó et al. 2021). These approaches frame the teaching and learning strategies explored in this study, which seeks to relate them to student profiles based on levels of self-regulation.

Drawing on these arguments and within this wider research context, our study aims to reveal different profiles of student learner based on their levels of self-regulation of learning, and to find out what ways of learning, teaching methodologies and assessment strategies are most valued by these learner profiles.

We will address the following research questions:

Q1. *What learner profiles are found among university students?*

Q2. *What characteristics define learner profiles, according to variables such as sex, academic year, study field, level of self-efficacy and study-related exhaustion?*

Q3. *What ways of learning, teaching methodologies and assessment strategies are most valued by learner profile?*

2 | Methods

This study was undertaken using a non-experimental transversal (*ex post-facto*) and quantitative methodological approach.

2.1 | Participants

The total sample included 697 undergraduate students from Comillas Pontifical University in Madrid (Spain), 57.7% of which were undertaking their first year in college and the remaining 42.3% were in their final year of study. This selection process aimed to secure a representative sample among newly arrived students and those students who had already experienced university life. The majority of respondents were women, accounting for 67.6%, while men made up 32.4%. Data was collected among students undertaking degrees in the fields of Education ($n=90$), Humanities and Social Sciences (Psychology, Social Work, International Relations, Translation) ($n=254$), Economics ($n=240$) and Engineering ($n=113$). Initially, a total of 808 students responded to the questionnaire. Of these, 100 were eliminated because they did not belong to the group selected for this study. In addition, 11 cases were eliminated because they answered the questionnaire insincerely or answered the control question incorrectly (devised to detect careless answers).

2.2 | Instruments

Self-regulation of learning was measured using the Inventory of Learning Styles (ILS, Vermunt 1994), applying its 15-item reduced version as employed by Räisänen et al. (2020). While the ILS was originally developed to assess learning styles and establish learning patterns (Vermunt and Vermetten 2004; Vermunt and Donche 2017), its scales related to self-regulation of learning have been widely used in research to examine students' self-regulatory processes (e.g., Räisänen et al. 2020). Specifically, we utilised the self-regulation subscales of the ILS to measure constructs closely related to learning regulation, including self-regulation of process, self-regulation of content, external regulation, and lack of regulation. This part of the instrument has four scales (self-regulation of process, self-regulation of content, external regulation and lack of regulation). Four items measured students' self-regulation of process; three items measured the self-regulation of content; four items measured external regulation and four items assessed lack of regulation. These responses contained a 7-point Likert type scale where 1 = totally disagree and 7 = totally agree.

To examine these scales, first, we carried out an exploratory factor analysis (EFA) by factoring the main axes and an Oblimin rotation (Table 1). The EFA revealed that the factorial structure resembled previous studies (Räisänen et al. 2020), which included four key factors: self-regulation of process, self-regulation of content, external regulation and lack of regulation which explained 49.6% of the total variance, KMO = 0.73; Bartlett $p<0.001$. Subsequently, a confirmatory factor analysis (CFA) was conducted to test the four-factor structure proposed by Räisänen et al. (2020) for the abbreviated version of the scale. The results indicated that the model showed an acceptable fit ($\chi^2(84)=245$, $p<0.001$, CFI = 0.885, TLI = 0.856, RMSEA = 0.052, SRMR = 0.048), supporting the overall structure of the instrument (Table S1). Latent factor correlations for the 15-item CFA model are presented in Table S2. Although inspection of the standardised loadings suggested that a small number of items had comparatively weaker loadings (Table S3), the original 15-item structure was retained to preserve the conceptual coverage of the construct and ensure comparability with previous research using this version of the scale.

The reliability coefficients obtained for the learning self-regulation scales ($\alpha=0.56$ for process self-regulation, $\alpha=0.64$ for content self-regulation, $\alpha=0.63$ for external regulation and $\alpha=0.59$ for lack of regulation) are considered moderate or low compared to conventional standards (Nunnally and Bernstein 1994). Nevertheless, our results are consistent with those reported by Räisänen et al. (2020), who also found moderate α coefficients for process self-regulation ($\alpha=0.64$), content self-regulation ($\alpha=0.66$) and lack of regulation ($\alpha=0.62$), Table 1.

Taken together, the results of the EFA and CFA suggest that the underlying factor structure is sufficiently stable and theoretically coherent for measuring the constructs of interest in the present sample. This interpretation produced a four-factor solution that aligns with previous studies (e.g., Räisänen et al. 2020). Although some reliability coefficients fell below the conventional 0.70 threshold (Nunnally and Bernstein 1994), they are consistent with those found in earlier studies using the same short version of the ILS and fall within the range considered acceptable for exploratory research or for scales with few items (Cortina 1993; Hair et al. 2019; Taber 2018).

TABLE 1 | Exploratory factorial analysis.

	Factors			
	1	**2**	**3**	**4**
Self-regulation of learning content				
In addition to the course requirements, I study other literature related to the content of the course	0.760			
I do more than I am expected to do in a course	0.683			
If I do not understand the subject matter, I search for more material related to the subject concerned	0.656			
		% variance		14.4
		α		0.64
External regulation				
I study according to the instructions given in the study material or provided by the teacher		0.772		
I experience the instructions and assignments given by the teacher as indispensable guidelines for my studies		0.756		
The instructions and the course objectives given by the teacher are important for me to know exactly what to do		0.737		
I study all the subject matter in the same order that it has been handled in the course		0.310		
		% variance		13
		α		0.63
Lack of regulation				
It is difficult for me to determine whether I have mastered the subject matter sufficiently			0.768	
I have noticed that I have trouble processing a large amount of subject matter			0.737	
I realise that I miss someone to fall back on in case of difficulties in studying			0.653	
I realise that the objectives of the course are too general for me to offer any support	0.369	−0.280	0.408	
		% variance		12
		α		0.59
Self-regulation of learning process and results				
To test my learning progress, I try to formulate the main points in my own words				0.794
To test whether I have mastered the subject matter, I try to think of examples and problems besides the ones given in the study material or by the teacher				0.621
When I am studying, I also pursue learning goals that have not been set by the teacher, the course or degree but by myself				0.395
When I have difficulty understanding particular subject matter, I try to analyse why it is difficult for m				0.475
		% variance		10.1
		α		0.56
% total variance	49.6			

[a]The structure matrix was carried out through Varimax rotation.

To measure study-related academic exhaustion among university students, we applied a version of the Study-Burnout Inventory (SBI-9, Salmela-Aro et al. 2009) used by Räisänen et al. (2020), which included three items ('I feel overwhelmed by my study work;'. 'I often sleep badly because of matters related to my study work;' 'I often brood during my free time over matters related to my study work') within a Likert scale of seven points between 1 = completely disagree and 7 = totally agree. The total variance was 72%, KMO = 0.71, Barlett $p < 0.001$ and $\alpha = 0.803$.

Our study also included an item used to measure self-efficacy from Torre (2006). Students responded to the statement 'Considering the difficulty of my degree, what I am learning and my own capabilities, I think I will be fine when I finish my degree' with a scale of 1 (I totally disagree) and 7 (I totally agree).

We also asked students to rate the value placed on different ways of learning taken from Seemiller and Grace's (2016) questionnaire within a scale of 1 (none) to 4 (a lot). Finally, students also had to value the usefulness of a number of different teaching methodologies and assessment strategies within a context of options between 1 (not useful at all) and 5 (very useful).

2.3 | Questionnaire Distribution and Data Collection

Once our University Research Ethics Committee had approved our study (ref. 21-10-2020), we contacted the course directors for each of the degrees to help us distribute and implement the questionnaire inside the classroom in online format. The questionnaire was collected during February and March 2023; the students had finished the mid-term evaluations and had already started the second term of the course, which allowed them to know and value their learning strategies. Students were selected using a convenience non-probability sampling method.

2.4 | Data Analysis

To evaluate the suitability of the instruments used, we analysed the Kaiser-Meyer-Olkin (KMO) measure, which assesses sampling adequacy for factor analysis by determining the proportion of variance attributable to underlying factors. We also applied Barlett's sphericity test to our sampling method to confirm that the data were suitable for EFA. We also undertook an EFA with the key component extraction method and Oblimin rotation. EFA was used to determine whether the theoretical dimensions outlined in the literature (Räisänen et al. 2020) are supported by the data, thereby establishing the structural validity of the measures. This process ensures that the scales accurately represent the factors of interest within the given context. In addition, a CFA was conducted to test the four-factor structure proposed by Räisänen et al. (2020) for the abbreviated version of the scale. The model was estimated using maximum likelihood estimation, and model fit was evaluated using standard fit indices (CFI, TLI, RMSEA, and SRMR; more details on Table S1). Additionally, EFA and CFA enhance the comparability of findings with previous studies, which is a critical component of this research. To analyse the internal consistency of scales which included seven response options, we used Cronbach α. To assess our items, we estimated the correlation coefficient between each item and the overall scale, if the item was eliminated (r Pearson). Finally, a cluster analysis was conducted to identify different profiles of learning regulation among students. First, a preliminary exploration was carried out to examine k-means solutions ranging from two to six clusters using standardised scores on the four regulatory dimensions (self-regulation of process, self-regulation of content, external regulation, and lack of regulation). The alternative solutions were compared in terms of convergence, cluster size distribution, separation between cluster centres, parsimony, and theoretical interpretability of the resulting profiles. Based on these criteria, the four-cluster solution was retained. K-means clustering was selected because it is well suited for large datasets and allows the identification of groups of cases with similar patterns across multiple standardised variables. These methods were selected to effectively manage large datasets while maintaining flexibility in grouping.

The comparison between two averages by sex was tested using Student's t-test. Cohen's d was used to measure the size effect, ANOVA to analyse differences according to field of study, and η^2 to measure magnitude differences. Pearson r was used for continuous variables and $\chi^2$with categorical variables and the contingency coefficient to assess the magnitude of the relationship (C). Variance homogeneity was analysed via Levene, normality with Shapiro–Wilk and non-parametric tests were carried out (U Mann Whitney and Kruskal Wallis) to confirm findings when the assumptions were not fulfilled, ensuring robustness in the results.

Analysis was carried out using IBM SPSS and JAMOVI 2.2.5 software and significant value was considered for $p < 0.05$.

3 | Findings

3.1 | Q1: What Learner Profiles Emerge Among University Students?

To answer this question, we undertook a cluster analysis that allowed us to reveal a number of key groups according to key dimensions of self-regulation of learning (self-regulation of process and content, external regulation and a perception of difficulty in self-regulation competencies), as shown in Figure 1. The analysis aimed to group students with similar patterns of learning regulation while maximising differences between groups. To achieve this, we explored k-means solutions ranging from two to six clusters using standardised scores on the four regulatory dimensions.

The four-cluster solution produced groups of adequate size ($n = 196$, $n = 182$, $n = 159$, and $n = 160$). Inspection of the cluster centres indicated differentiated patterns across the four regulatory dimensions. The emergence of four learner profiles is theoretically consistent with Vermunt's model of learning patterns, which identifies four recurrent configurations of regulation processes, learning strategies, and learning orientations among students (Vermunt 1998; Vermunt and Donche 2017; Vermunt and Vermetten 2004). This four-profile structure has also been supported in recent empirical studies examining self-regulation patterns in higher education (Ciraso-Calí et al. 2025).

FIGURE 1 | Clusters with average standardised scores.

Compared with alternative solutions, the four-cluster model provided the best balance between parsimony and interpretability. The two-cluster solution mainly reflected a broad high-versus-low distinction across the regulatory variables, whereas the three-cluster solution still included a very large cluster and less clearly differentiated profiles. The five- and six-cluster solutions also converged but mainly resulted in the fragmentation of existing profiles without yielding substantively new or clearly interpretable patterns.

The first cluster (C1) is made up of 28.12% of the sample and is characterised by its high average score for process and content self-regulation, as well as external regulation. C1 obtains a low score in the perception of difficulty in self-regulation. This cluster represents students with high levels of self-regulation of learning and uptake of external instructions. We have called them strategic learners. The second cluster (C2) is made up of 26.11% of the sample and its principal characteristics include low scores for self-regulation and external regulation and an above average score for problems in self-regulation. We have classed these as non-strategic learners. The third cluster (C3) is comprised of 22.81% of the sample. This cluster presents low scores in self-regulation and above average scores in external regulation, which describes students who are regulated primarily based on external instructions. We have called them external strategic learners. The fourth and final cluster (C4) includes 22.96% of the sample. This cluster is characterised by its above average scores in all four dimensions. This group shows competencies in self-regulation and positive responsiveness to external instructions but also faces challenges or perceives difficulty in applying these skills effectively, often linked to anxiety or external pressures. We have called them anxious strategic learners.

3.2 | Q2: What Key Characteristics Define Learner Profiles According to Sex, Academic Year, Area of Study, Academic-Related Exhaustion and Levels of Self-Efficacy?

First of all, as shown in Table 2, although there are higher levels of men among non-strategic and external strategic learners, and higher levels of women among strategic and anxious strategic learners, our data overall does not reveal significant differences ($p > 0.05$) according to sex between learner profiles.

Secondly, our data points to higher numbers of first year students among anxious strategic and external strategic learners, while final year students display a higher percentage of non-strategic and strategic learners. Having said that, findings do not show significant differences ($p > 0.05$) according to academic year.

Thirdly, our data reveals significant differences ($p < 0.01$) in relation to students' area of study. Those studying Education have a higher percentage of non-strategic and external strategic learners. In the field of Humanities and Social Sciences and Economics, we find more anxious strategic and non-strategic learner students. In the field of Engineering, on the other hand, we find more external strategic and strategic students.

Fourthly, our study also explored the relationship between study-related exhaustion and learner profiles. We found significant differences ($p < 0.001$), especially among anxious strategic learners, who display higher scores of study-related exhaustion than the rest of learners. Strategic learners, on the other hand, display the lowest levels of study-related exhaustion, followed by non-strategic learners and external strategic learners.

Finally, strategic students display the highest levels of self-efficacy ($p < 0.001$). Learners with the lowest levels of self-efficacy, from low to high, include non-strategic learners, anxious learners and external strategic learners.

3.3 | Q3: What Ways of Learning, Teaching Methodologies and Assessment Strategies Are Most Valued by Students Based on Their Learner Profiles?

As shown in Figure 2, students generally seem to value learning by doing, learning with peers, or learning autonomously, whereas the least valued way of learning is listening to a lesson.

TABLE 2 | Description of learner regulation profiles.

		Cluster 1: Strategic	Cluster 2: Non-strategic	Cluster 3: External strategic	Cluster 4: Anxious strategic	Prev
n		196	182	159	160	
Sex χ^2: 4.98 df: 6 $p > 0.05$	Men	28.6%	38.5%	31.4%	30.6%	
	Women	71.4%	61.0%	67.9%	68.8%	
	Prefer not to say	0.0%	0.5%	0.6%	0.6%	
Year of Study χ^2: 6.32 df: 3 $p > 0.05$	First year	54.1%	53.8%	58.5%	65.6%	
	Final year	45.9%	46.2%	41.5%	34.4%	
Knowledge field χ^2: 25.58 df: 9 $p < 0.01$ $C = 0.19$	Education	12.8%	13.2%	14.5%	11.3%	
	Social Sciences	32.7%	39.0%	30.2%	44.4%	
	Economics	33.2%	37.4%	31.4%	35.6%	
	Engineering	21.4%	10.4%	23.9%	8.8%	
Study-related exhaustion $F = 10.46$ df = 3;693 $p < 0.001$ $\eta^2 = 0.043$	Mean	4.1122	4.1667	4.2138	4.9042	C4 > C1, C2, C3
	SD	1.45	1.50	1.54	1.44	
Self-Efficacy $F = 13.37$ df = 3;693 $p < 0.001$ $\eta^2 = 0.055$ $H = 36.4$ $p < 0.001$[a]	Mean	6.13	5.50	5.77	5.65	C1 > C2, C4
	SD	0.849	1.116	1.055	1.041	

[a]When the assumption of homogeneity of variances is not met, the result is confirmed with the Kruskal-Wallis test (H).

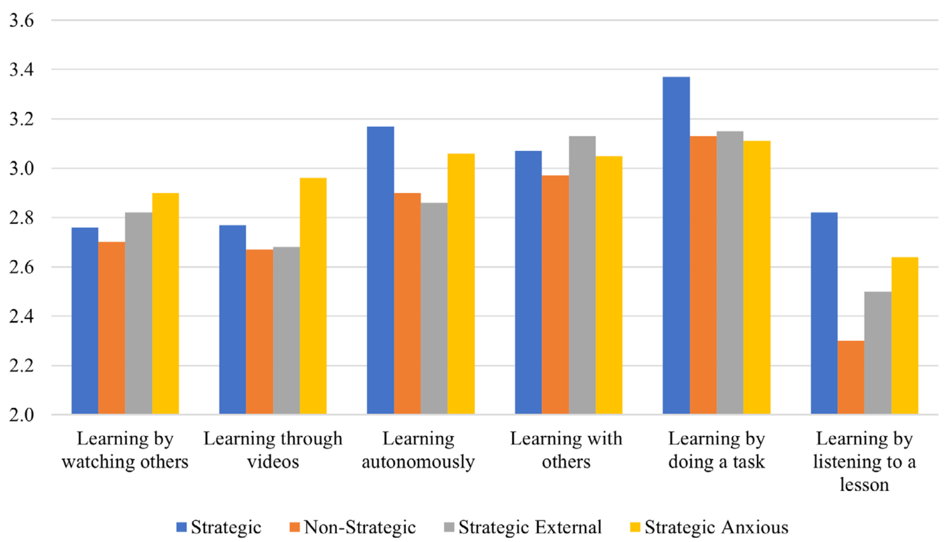

FIGURE 2 | Ways of learning preferences.

TABLE 3 | Ways of learning preferences by regulation profiles.

		Cluster 1: Strategic	Cluster 2: Non-strategic	Cluster 3: External strategic	Cluster 4: Anxious strategic	Prev
n		196	182	159	160	
Learning by watching others $F=2.34$ $\mathrm{df}=3;693$ $p>0.05$ $\eta^2=0.010$	Mean SD	2.76 0.717	2.70 0.722	2.82 0.838	2.90 0.711	
Learning through videos $F=4.67$ $\mathrm{df}=3;693$ $p<0.01$ $\eta^2=0.020$	Mean SD	2.77 0.773	2.67 0.780	2.68 0.782	2.96 0.811	C4 > C2, C3
Learning autonomously $F=5.84$ $\mathrm{df}=3;693$ $p<0.001$ $\eta^2=0.025$	Mean SD	3.17 0.756	2.90 0.835	2.86 0.826	3.06 0.779	C1 > C3 and C2
Learning with others $F=1.19$ $\mathrm{df}=3;693$ $p>0.05$ $\eta^2=0.005$	Mean SD	3.07 0.745	2.97 0.817	3.13 0.718	3.05 0.751	
Learning doing a task $F=5.48$ $\mathrm{df}=3;693$ $p<0.01$ $\eta^2=0.023$	Mean SD	3.37 0.647	3.13 0.724	3.15 0.695	3.11 0.749	C1 > C4, C2 and C3
Learning by listening to a lesson $F=13.37$ $\mathrm{df}=3;693$ $p<0.001$ $\eta^2=0.055$	Mean SD	2.82 0.821	2.30 0.800	2.50 0.848	2.64 0.819	C1 > C2 and C3 C2 < C4

According to Table 3, 'learning by doing a task' is most valued by strategic students ($p<0.01$), who score significantly higher than other profiles. No significant differences ($p>0.05$) were found between learner profiles for 'learning with others,' although external strategic students show slightly higher averages.

For 'learning autonomously,' strategic students scored significantly higher than external strategic and non-strategic students ($p<0.01$), with no differences observed compared to anxious learners. No significant differences ($p>0.05$) were found for 'learning by watching others,' although anxious and external strategic students displayed slightly higher preferences. Regarding 'learning through videos,' anxious students scored significantly higher than non-strategic and external strategic students ($p<0.01$), with no differences noted between anxious and strategic students. Lastly, for 'learning by listening to a lesson,' strategic students achieved the highest scores ($p<0.01$), while anxious students also scored higher than non-strategic students ($p<0.01$).

As shown in Figure 3, students most value teaching methodologies such as problem-based learning and case studies, whereas traditional lectures and flipped classrooms are the least valued. Traditional lectures accompanied by visual aids are moderately valued. According to Table 4, strategic students rate traditional lectures significantly higher than non-strategic and external strategic students ($p<0.001$). Similarly, traditional lectures with visual aids are also more highly valued by strategic students compared to non-strategic students ($p<0.01$). Problem-based learning is most valued by strategic students, who rate it significantly higher than non-strategic and anxious students ($p<0.001$). External strategic students also rate it higher than non-strategic students ($p<0.001$). Similarly, case studies are

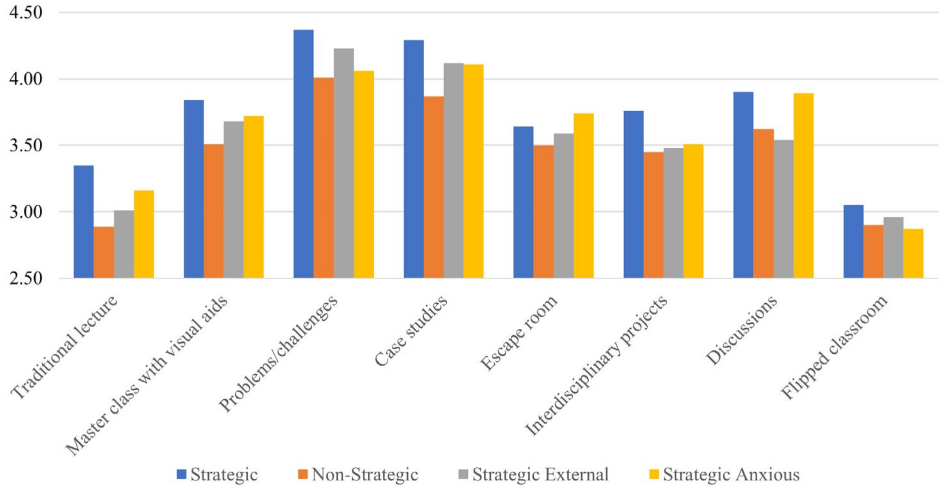

FIGURE 3 | Teaching methodology preferences.

more highly valued by strategic students than by non-strategic students ($p < 0.001$), with external strategic students also rating them higher than non-strategic students ($p < 0.001$).

No significant differences were observed for gamification activities, such as Escape Rooms ($p > 0.05$), although anxious students showed slightly higher averages. For interdisciplinary projects, strategic students valued them more than non-strategic students ($p < 0.01$). For debates, strategic students scored higher than external strategic students ($p < 0.001$), and anxious students also rated debates higher than external strategic students ($p < 0.01$). Strategic students displayed the highest averages for flipped classrooms; however, no significant differences were found across profiles ($p > 0.05$). These results highlight strategic students' preferences for structured and problem-solving methodologies, whereas gamification and flipped classrooms show less distinction across profiles.

Regarding students' valuation of assessment strategies, as shown in Figure 4, oral exams are the most valued, followed by one-minute papers at the end of class and portfolios, diaries, or reports. The most valued assessment strategies include practical case studies, both individual and group projects, and open-ended exams.

We found no significant differences ($p > 0.05$) in relation to case study exams as an assessment strategy based on learner profiles, Table 5. Strategic students value open-ended exams more positively than external strategic students, anxious students, and non-strategic students ($p < 0.05$). Significant differences ($p < 0.05$) only appear between strategic and non-strategic students in their perceived value of individual and group projects as an assessment strategy. No significant differences ($p > 0.05$) were found in their assessment of multiple choice tests based on learner profiles. Portfolios are more valued by anxious students than non-strategic students ($p < 0.05$). There were no differences ($p > 0.05$) in students' assessment of one-minute papers. While we found no differences between our four groups when applying Kruskal Wallis, when applying Snedecor's F, we did find differences between strategic and external strategic students in their perceived value of oral exams, where the former value oral exams more positively than the latter. At any rate, oral exams are the least valued assessment strategy by all learner profiles.

4 | Discussion

Vermunt and Vermetten (2004) point out that the self-regulation of learning involves those processes that students apply to manage and guide their own learning. These processes are essential to determine how students approach different learning tasks and how they manage both cognitive and metacognitive resources to realise their goals. Our study highlights the need to understand university students' different learner profiles, with a specific focus placed on revealing a different usage of self-regulation of learning strategies and their learning preferences. We argue that drawing on a better understanding of different self-regulation of learning profiles, as well as their preferences when it comes to learning ways, teaching methodologies and assessment strategies, our findings could help us reflect upon how we might improve student satisfaction and academic performance.

First of all, our study identifies four learner profiles (strategic, non-strategic, external and anxious), each of which is characterised by a diverse set of significant differences in relation to their capacity for self-regulation, use of external resources and difficulties in regulating their own learning. These different profiles point to self-regulation strategies as a key variable that influences directly students' ability to manage more effective and quality learning processes, a finding that echoes previous studies that highlight self-regulation strategies as key predictors of academic success (García and Pintrich 1994; Hadwin et al. 2017; Hattie and Timperley 2007; Panadero 2017; Zimmerman and Moylan 2009).

Secondly, our study investigated the relationship between learner profiles and a number of key variables, including sex, academic year of study, area of study, study-related exhaustion and levels of self-efficacy among students. Our literature review found no consensus regarding the relationship between sex and self-learning processes (Liu et al. 2021; Malik and

TABLE 4 | Teaching methodology preferences by regulation profiles.

		Cluster 1: Strategic	Cluster 2: Non-strategic	Cluster 3: External	Cluster 4: Anxious	Prev
n		196	182	159	160	
Traditional lecture $F = 6.36$ $df = 3;694$ $p < 0.001$ $\eta^2 = 0.027$ $H = 18.321$ $p < 0.001$[a]	Mean SD	3.35 1.073	2.89 1.061	3.01 1.131	3.16 1.024	C1 > C2 C3
Traditional lecture with visual aids $F = 4.74$ df = 3;694 $p < 0.01$ $\eta^2 = 0.020$ $H = 14.08$ $p < 0.01$	Mean SD	3.84 0.860	3.51 0.925	3.68 0.888	3.72 0.802	C1 > C2
Problem based learning $F = 10.80$ df = 3;694 $p < 0.001$ $\eta^2 = 0.045$ $H = 28.07$ $p < 0.001$	Mean SD	4.37 0.607	4.01 0.711	4.23 0.636	4.06 0.811	C1 > C2. C4 C2 < C3
Case studies $F = 9.00$ df = 3;694 $p < 0.001$ $\eta^2 = 0.038$	Mean SD	4.29 0.706	3.87 0.876	4.12 0.756	4.11 0.800	C1 > C2 C2 < C3
Gamification—for example, escape room $F = 1.10$ df = 3;694 $p > 0.05$ $\eta^2 = 0.005$	Mean SD	3.64 1.206	3.50 1.227	3.59 1.283	3.74 1.161	
Interdisciplinary projects $F = 3.96$ df = 3;694 $p < 0.01$ $\eta^2 = 0.018$	Mean SD	3.76 0.889	3.45 0.948	3.48 0.987	3.51 0.972	
Debates $F = 5.79$ df = 3;694 $p < 0.001$ $\eta^2 = 0.025$ $H = 15.42$ $p < 0.01$	Mean SD	3.90 0.949	3.62 1.017	3.54 1.109	3.89 0.938	C1 > C3 C4 > C3
Flipped classroom $F = 0.72$ df = 3;694 $p > 0.05$ $\eta^2 = 0.004$	Mean SD	3.05 1.099	2.90 1.210	2.96 1.146	2.87 1.040	

[a]When the assumption of homogeneity of variances is not assumed, the result is confirmed with the Kruskal-Wallis test (H).

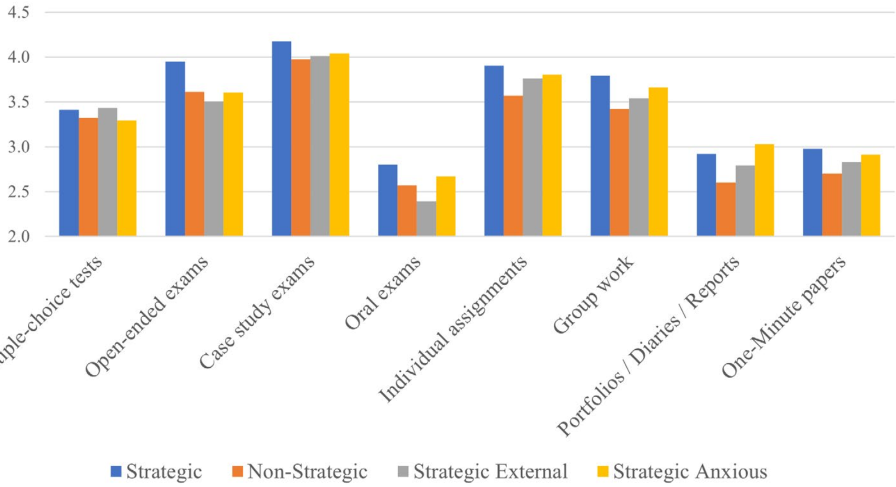

FIGURE 4 | Assessment strategy preferences.

Parveen 2019; Zimmerman and Martinez-Pons 1990). Agha and Rehman (2016) and Wolters and Pintrich (1998), for example, point to key differences in the use of cognitive strategies between men and women (in favour of the latter). On the other hand, findings from our study reveal no significant differences between learner profiles according to sex. In addition, our analysis shows no significant differences based on year of study either, findings which echo a study by Räisänen et al. (2020), Räisanen et al. (2021). As regards field of study, our findings did reveal significant differences between students from different academic disciplines, something we argue could help inform educational interventions. According to our findings, the fields of Education and Humanities and Social Sciences include less strategic and more anxious learner profiles, which suggests that these disciplines could benefit from the use of more interactive and participative learning strategies to promote greater self-regulation among their students (Melchor Gutiérrez and Tomás 2018). Finally, we would also highlight the differences between learning profiles in relation to self-efficacy and study-related exhaustion. Students with higher levels of belief in their own abilities obtain highest scores among strategic learners, while the other profiles display lower levels of self-efficacy, specially non-strategic students. As expected, study-related exhaustion is higher among anxious strategic students. For example, recent studies on the effects of the COVID-19 pandemic (Johnson and Li 2022; Smith and Li 2021) have shown an increase in anxiety and study-related fatigue, particularly among students with lower self-regulation skills. Independently from academic success, a variable we could not evaluate, these variables (self-efficacy and study-related exhaustion) play a key role in students' self-regulation of learning, a tendency also found in other studies such as Efklides (2014), González et al. (2017) and Pajares (2008). We conclude that, first of all, if we could identify anxious strategic learners among our students, we might be able to offer more effective ways to help them manage anxiety; and secondly, that non-strategic learners would benefit from further monitoring processes and greater academic feedback (Panadero 2023).

A third contribution of the study involves the analysis of how different learner profiles evaluate different learning strategies. Overall, students prefer to learn by doing rather than by listening to a lecture (passively); they prefer active and applied teaching methodologies, such as problem solving and project-based learning. In line with other studies which point to active methodologies as the most effective for current generations (Fodor and Jaeckel 2018; Mohr and Mohr 2017; Puiu 2017; Seemiller and Grace 2017), in our study, this preference for active and applied methods is especially true for students with a strategic learner profile. The integration of digital resources, such as videos and interactive tools, aligns with this preference, particularly for anxious students who highly value video-based learning ($p < 0.01$). These tools can enhance engagement and address the needs of non-strategic or external strategic learners by providing clear guidance and feedback through interactive calendars and task management applications (Broadbent 2017; Greenwood 2011; Szabó et al. 2021). The findings may also be linked to studies suggesting that active methodologies are more effective in enhancing self-regulation of learning (see, for example, Hattie (2011) and Kolb (2014)). On the other hand, it is also important to highlight that students with non-strategic or external strategic learner profiles might need additional support structures to benefit from such methodologies, such as clear guidance and feedback (Brown et al. 2014; Dawson et al. 2023; De la Fuente et al. 2022; Panadero 2023; Yan et al. 2023); these can be offered through digital environments including planning applications such as interactive calendars and task management applications (Broadbent 2017). Finally, in line with findings from a systematic review by Evans et al. (2019), our study also revealed the flipped classroom as the least valued methodology by students.

Our study also analysed students' perceived value of assessment strategies. Our findings reveal an overall preference for practical and applied assessment methods, such as group work and case studies. Such findings echo other studies, whose works highlight the benefits of practical assessment tests, self-evaluation and immediate feedback for improving students' self-regulation of learning processes (Brown et al. 2014; Dawson et al. 2023; De la Fuente et al. 2022; Mohr and Mohr 2017; Panadero 2023; Yan et al. 2023). In agreement with some other studies, such as Brown et al. (2014), Ivala and Kioko (2020) and Murphy (2021), our study also concludes

TABLE 5 | Assessment strategy preferences by regulation profiles.

		Cluster 1: Strategic	Cluster 2: Non-strategic	Cluster 3: External	Cluster 4: Anxious	Prev
n		196	182	159	160	
Multiple choice tests	Mean	3.41	3.32	3.43	3.29	
$F=0.62$ df = 3;696 $p>0.05$ $\eta^2=0.003$	SD	1.066	1.156	1.065	1.179	
Open-ended exams	Mean	3.95	3.61	3.50	3.60	C1 > C3 C4 and C2
$F=8.25$ df = 3;696 $p<0.001$ $\eta^2=0.035$ $H=25.08$ $p<0.001$	SD	0.880	0.896	0.935	0.960	
Case study exams	Mean	4.17	3.97	4.01	4.04	
$F=2.15$ df = 3;696 $p>0.05$ $\eta^2=0.009$	SD	0.788	0.905	0.813	0.782	
Oral exams	Mean	2.80	2.57	2.39	2.67	C1 > C3
$F=2.98$ df = 3;696 $p<0.05$ $\eta^2=0.014$ $H=4.38$ $p>0.05$	SD	1.262	1.342	1.151	1.270	
Individual assignments	Mean	3.90	3.57	3.76	3.80	C1 > C2
$F=3.69$ df = 3;696 $p<0.05$ $\eta^2=0.016$	SD	0.948	1.050	0.944	1.014	
Group work	Mean	3.79	3.42	3.54	3.66	C1 > C2
$F=4.18$ df = 3;693 $p<0.01$ $\eta^2=0.018$	SD	1.044	1.121	1.066	0.967	
Portfolios/diaries/reports	Mean	2.92	2.60	2.79	3.03	C4 > C2
$F=4.08$ df = 3;693 $p<0.01$ $\eta^2=0.019$	SD	1.105	1.229	1.214	1.168	
One-minute papers	Mean	2.98	2.70	2.83	2.91	
$F=1.53$ df = 3;696 $p>0.05$ $\eta^2=0.007$	SD	1.233	1.231	1.291	1.290	

[a]When the assumption of homogeneity of variances is not assumed, the result is confirmed with the Kruskal-Wallis test (H).

that the differences between learner profiles, regarding their perceived value of assessment methods, suggest that a greater personalisation and diversification of assessment methods could be useful to respond to a diverse set of specific needs among our students.

5 | Conclusion

Our study highlights the diversity of self-regulated learning profiles among university students. Understanding the relationship between these profiles and their preferences for learning, teaching and assessment strategies can help improve approaches that enhance academic performance for more students. For instance, strategic learners benefit most from active methodologies, such as problem-solving and case studies, which are associated with improved self-regulation and learning outcomes (Hattie 2011; Kolb 2014). Additionally, our findings suggest that creating tutorial spaces—both face-to-face and online—may help non-strategic and anxious learners identify key milestones in their learning and develop planning skills to meet academic demands. These spaces can incorporate tools such as interactive calendars and task management applications (Broadbent 2017) to provide the structured guidance and feedback these learners require (De la Fuente et al. 2022; Yan et al. 2023). For external strategic learners, educational interventions should focus on fostering greater academic autonomy, regardless of the method employed, to ensure they fully benefit from active learning approaches. In particular, students with lower levels of self-regulation—such as non-strategic and anxious learners—may benefit from short workshops, mentoring programmes (with teachers and peers), or embedded modules focused on learning strategies, planning, and emotional regulation. Such interventions can be integrated into existing curricula or offered through academic support services and are designed to foster autonomy, metacognitive skills, and academic resilience over time.

While future research could expand on our findings, it is essential to recognise the value they offer at this moment. Our study provides a solid foundation for teachers to adapt their teaching methods to the current needs of students, especially as self-regulated learning is key to academic success. Now is a critical time to apply this knowledge in ways that benefit students' achievement.

Arguably, recognising and responding to different teaching methodologies and preferences could help us improve our students' academic performance, satisfaction levels, and well-being, enhancing their chances of becoming ready for future challenges in a more effective manner.

A key strength of our study, in addition to its large sample, lies in its analysis that includes different areas of study. A possible limitation of this study is that it involved students from only one Spanish university, which may limit the generalisability of the findings to other contexts. Our study employed a convenience non-probability sampling method which, while practical for obtaining data from a large number of participants, introduces potential biases. Consequently, the generalisability of our findings beyond the context of Spanish university students from a single institution should be approached with caution. Future studies could address these limitations by expanding the research to include participants from multiple universities and cultural contexts, thereby enhancing the robustness and applicability of the results. As such, we would like to propose further research that involves more universities, preferably from different countries. For instance, comparative studies involving universities in Northern European countries, such as Finland or Sweden—where self-regulation and collaborative learning are emphasised—could offer insights into how different educational models influence learning strategies. Similarly, exploring contexts in Asian countries like Japan or South Korea, where academic rigour and discipline are highly valued, might reveal contrasting profiles. Including universities from Latin American countries, such as Mexico or Brazil, could also shed light on the role of collectivist cultural values in shaping learning approaches. Finally, developing longitudinal studies would allow us to capture processes of adaptation and change at university; that is, what we would like to see is an evolution towards a greater number of self-regulated and strategic students in the course of their academic study at university, and beyond. A personalised learning journey emerges as one of the most urgent and necessary challenges facing tertiary level educational institutions nowadays, especially within the fields of Humanities and Social Sciences, study fields that currently appear to include fewer 'ideal learner' profiles.

Author Contributions

M. Hernández-Arriaza: data curation, formal analysis, funding acquisition, investigation, methodology, software, supervision, visualization, writing – original draft. **G. Aza-Blanc:** conceptualization, funding acquisition, investigation, project administration, resources, supervision, visualization, writing – original draft, writing – review and editing. **I. Muñoz-San Roque:** conceptualization, data curation, software, methodology, validation, investigation, funding acquisition, writing – original draft, writing – review and editing, project administration, formal analysis, supervision, resources. **J. R. Martínez-Fernández:** conceptualization, investigation, supervision, validation, writing – original draft, writing – review and editing. **E. Fernández:** validation, supervision, writing – original draft, writing – review and editing.

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The authors have nothing to report.

Ethics Statement

The Research Ethics Committee of the Comillas Pontifical University approved this study (ref. 21-10-2020).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** contains the model fit indices for the 15-item confirmatory factor analysis model. **Table S2:** Contains the latent factor correlations for the 15-item confirmatory factor analysis model. **Table S3:** Contains the standardised factor loadings for the 15-item CFA model.