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Integrating self-regulated learning and individual differences in the prediction of university academic achievement across a three-year-long degree

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Abstract
The study investigated the joint contribution of the self-regulated learning (SRL) and individual differences approaches to the prediction of university students' grade point average (GPA) obtained at three separate time points throughout their degree (3 years). We assessed cognitive (i.e., previous academic performance, cognitive ability, and cognitive SRL strategies) and non-cognitive variables (i.e., personality, trait emotional intelligence, motivation, and non-cognitive SRL strategies) in a sample of Spanish undergraduates. Results showed that GPA correlated with previous academic performance (i.e., combination of high school's GPA and college admission test score), academic self-efficacy, academic engagement, SRL strategies, and conscientiousness. Hierarchical regression analyses indicated that non-cognitive factors (i.e., academic engagement, academic self-efficacy, regulation of behavior and context, and conscientiousness) alone explained 17–25% of the variance in GPA across three years, and previous academic performance accounted up to an additional 25% of the variance, jointly reaching an explained variance of up to 50% in GPA. Specifically, academic engagement and regulation of behavior and context demonstrated incremental validity over and above cognitive predictors such as previous academic performance, inductive reasoning and regulation of cognition and metacognition. The role of intelligence, whether cognitive or emotional, was not as obvious as a predictor. Two nested structural equation models explained about 27–29% of the variance in a latent GPA factor exclusively from a proxy of a global variable of non-cognitive factors as a latent predictor, which is a novel and promising proof of its robust criterion validity. Implications and recommendations for future studies are discussed.

Keywords Academic performance · Conscientiousness · Individual differences · Self-regulated learning · Noncognitive skills

Azevedo (2020) highlighted that on the pursuit of a unified theory of metacognition and self-regulated learning (SRL), the study of individual differences must be incorporated, since "there is a need for more research on the role of motivational processes (e.g., self-

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efficacy and regulatory skills), emotional processes (e.g., emotion regulation skills), personality traits, working memory capacity, etc." (Azevedo, 2020, p. 95). From a different but complementary perspective, Jensen (1989) highlighted that the historical separation of the study of learning and of individual differences is seen as an anomaly in the development of scientific psychology. In fact, those few studies integrating these two perspectives indicate that taking into account both the SRL and individual differences may provide a better understanding of students' academic achievement than either one alone (De Feyter et al., 2012; Wolters & Hussain, 2015). In the same vein, De Raad & Schouwenburg (1996) emphasized the desirability of conducting integrated research including competing predictors of academic performance (AP) derived from different theoretical frameworks in a coherent system. Thomas et al., (2017) also advocated the need for a broader perspective in which multiple factors in higher education are integrated in concert, including different predictors from the affective domain.

Despite the prominent role of intelligence or general cognitive ability as a general predictor of AP (Galla et al., 2019; Kuncel & Hezlett, 2010; Richardson et al., 2012), some robust investigations indicate that greater intelligence does not imply higher AP. Hence, the positive association between intelligence and AP may not be linear nor exempt from several moderating factors (e.g., Chamorro-Premuzic et al., 2009; Díaz-Morales & Escribano, 2013). As we have pointed out, some authors (Jensen, 1989; De Raad & Schouwenburg, 1996; Thomas et al., 2017; Wolters & Hussain, 2015) emphasize the importance of an integrative approach to predict AP, combining both cognitive and non-cognitive variables. In their key meta-analysis, Richardson et al., (2012) observed that, in addition to SRL, within the individual differences perspective, the so-called non-cognitive factors (Wechsler, 1943; Heckman & Kautz, 2012) such as personality traits such as conscientiousness (Poropat, 2009), emotional intelligence (EI; MacCann et al., 2020), and motivation are individual difference variables usually associated with university AP. In their book chapter, Pintrich & Zusho (2007) also provided a conceptual framework for student motivation and SRL, which consists of personal characteristics, classroom context, motivational processes, self-regulatory processes, and outcomes. Pintrich & Zusho (2007) highlighted the importance of personality differences in addition to the regulation of affect and motivation in the SRL process. Some studies have integrated, to some extent, these individual differences within the SRL framework. For example, Bidjerano & Dai (2007) found that SRL strategies mediated the effect of personality on academic achievement. However, to our knowledge, no study examined the specific role of trait EI within this framework. Thus, the relationship between the SRL framework and both conscientiousness and trait EI remains under-studied, and the present study aims to provide a unique contribution in this direction.

The first purpose of the present work is twofold: on the one hand, to provide a parsimonious but tentative framework with which to integrate the SRL perspective and the perspective of individual differences, and, on the other hand, to explore the predictive power of a selected combination of variables from each of these approaches on university AP as a partial test of the application of this theoretical framework to the prediction of university AP. The second purpose is to also focus on non-cognitive factors combining as a subset of less studied individual differences in the context of university AP, in particular conscientiousness and trait EI, together with SRL variables such as academic engagement and academic self-efficacy.

SRL in the prediction of AP

SRL is a core conceptual framework to understand the cognitive, motivational, and emotional aspects of learning (Panadero, 2017). According to the theory of SRL (Pintrich, 2000, 2004; Zimmerman, 1990), high levels of metacognition and learning-appropriate cognitions, motivations, and behaviors are predictive of learning and higher AP, possibly over and above intelligence in some cases (Minnaert & Janssen, 1998). In particular, a meta-analysis by Ohtani & Hisasaka (2018) revealed an average correlation of $r = .20$ between SRL (measured by the Motivated Strategies for Learning Questionnaire or MSLQ; Pintrich et al., 1991) and AP. More recently, Kickert et al., (2019) specifically underlined the role of motivational and self-regulatory factors and confirmed that their relations with university AP are not only strong, but relatively independent of two different assessment policies in a joint sample of psychology and education university students.

The first model of SRL developed by Zimmerman (the Triadic Analysis of SRL) integrated the interaction of three levels of SRL, namely the environment, the behavior and the person (Zimmerman, 1989). When referring to the "person", Zimmerman focuses on individual strategies rather than the personal predispositions influencing their use. Other authors grounded in Zimmerman's theory, such as Efklides (2011) and Kuhl (2000) are more similar to our approach in the sense that they explicitly recognize the prominent role of personal characteristics, including cognitive and non-cognitive traits, such as emotional self-control or trait rumination.

The second model by Zimmerman, the cyclical model of SRL (Zimmerman & Moylan, 2009), represents the interrelation of metacognition and motivational processes through three major phases, namely forththought, performance, and self-reflection. These three phases mirror those of Printich's (2000): phase 1 (forethought, planning and activation), phase 2 (monitoring), phase 3 (control), and phase 4 (reaction and reflection). For the purpose of this study, we adopted Pintrich's (2004) model because it explicitly acknowledges the influence of personal characteristics and individual differences in the SRL process.

Non-cognitive predictors of AP

While SRL strategies allow for the regulation of cognition, motivation, affect, behavior and context, a content examination of the gold standard measure of learning strategies (i.e., MSLQ) shows greater weight on the regulation of cognition and metacognition, as well as behavior and context. The present study contributes to the examination of the complementary role of non-cognitive factors in the regulation of motivation and affect.

The role of non-cognitive factors or *soft skills* is pervasive in cognition and metacognition processes (e.g., Heckman & Kautz 2012; Román-González et al., 2018). Research has indicated that non-cognitive factors may directly or indirectly predict university AP (e.g., Heckman & Kautz 2012; Putwain et al., 2019; Richardson et al., 2012; Robbins et al., 2004). The five-factor model of personality has been proposed as a comprehensive operationalisation of non-cognitive factors or soft skills by Borghans et al., (2008). This model is a taxonomy that consists of five categories of broad personality dimensions, also known as the "Big Five", namely openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (see Goldberg 1993 for a historical overview). Several studies have explored the relationship between the Big Five traits and AP, and conscientiousness has been the most consistent significant predictor (e.g., Hakimi et al., 2011; Sorić et al., 2017; Wagerman & Funder, 2007), showing predictive validity over and above cognitive ability (Poropat, 2009). Conscientiousness is closely related to motivation and drive (Chamorro-Premuzic & Furnham, 2003; Siegling & Petrides, 2016), given that is a propensity associated with persistence, self-discipline, and achievement motivation (Román-González et al., 2018). Openness to experience has also been shown to be relevant to AP (e.g., Komarraju et al., 2011), while extraversion, agreeableness, and neuroticism have shown less persistent and weaker links with AP (e.g., Poropat 2009).

Emotional intelligence (EI) is interpreted as part of personality in the meta-analysis by Richardson et al., (2012). Two predominant theoretical models of emotional intelligence (EI) in the literature are trait EI and ability EI (Pérez-González et al., 2020). Trait EI, or trait emotional self-efficacy, is conceptualized as a constellation of dispositions and self-perceptions assessed using questionnaires and rating scales (Petrides et al., 2007b), whereas ability EI is conceptualized as an emotion-related cognitive ability best assessed using maximum performance tests (Mayer & Salovey, 1997). Meta-analyses and other research studies have supported the theoretical distinction between trait and ability EI (Joseph & Newman, 2010; Martins et al., 2010), including a study by Qualter et al., (2012) that found that trait and ability EI differentially predicted AP in a longitudinal, school-based study, further corroborating their theoretical distinction. Using trait EI to predict AP might be advantageous since it taps into emotion-related constructs that are not well covered by existing personality trait taxonomies (Pérez-González & Sanchez-Ruiz, 2014). This is important since trait EI has already shown incremental validity over cognitive ability, personality traits, and self-concept in the prediction of AP (Ferrando et al., 2011; Sanchez-Ruiz et al., 2013; Sanchez-Ruiz & El-Khoury, 2019), despite weak to moderate effect sizes (Petrides et al., 2018). This is corroborated by a meta-analysis by MacCann et al., (2020) which found trait EI to show incremental validity in the prediction of AP over and above intelligence and conscientiousness. However, the average correlation between trait EI and AP has not reached the thresholds of $r = .15$ and $r = .20$, according to Richardson et al.'s (2012) and MacCann et al.'s (2020) meta-analyses, respectively, so it does not yet appear to be an established predictor. For a review on the recent developments of trait EI research, see Petrides et al., (2016).

Academic self-efficacy is a robust predictor of AP as a motivation-related construct that consists of one's beliefs in one's ability to succeed academically. Academic self-efficacy has consistently shown to predict AP over and above other variables (Bandura et al., 1996; Lee et al., 2014; Richardson et al., 2012; Multon et al., 1991). For instance, Zuffianò et al., (2013) has shown self-efficacy to predict high school AP over and above previous AP, intelligence, personality traits, gender, socioeconomic status, and self-esteem.

Additionally, academic engagement is another promising non-cognitive predictor. It is a motivation-related construct that refers to a positive, persistent, and pervasive work-related state, characterized by vigor, dedication, and absorption (Schaufeli et al., 2002b). Several studies suggested a positive association between academic engagement and academic success in school and university (e.g., Schaufeli et al., 2002a). Although it has been a less studied construct in the SRL framework, academic engagement is in line with the taxonomy of self-regulation of learning areas (Pintrich, 2004), since academic engagement encompasses both the regulation of motivation (i.e., absorption and engagement) and affect (i.e., vigor).

A Novel and Eclectic Framework

The meta-analysis by Richardson et al., (2012) showed the need for a comprehensive theoretical and applied framework for the different psychological variables associated with AP. Nonetheless, this meta-analysis, despite it is regarded as a modern milestone (e.g., Ferrão & Almeida 2019), organized almost 40 psychological correlates of university AP in arbitrary and non-exclusive categories, which does not facilitate the construction of integrative models and the design of theory-driven empirical research. Pintrich (2004) described five general SRL areas: cognition, motivation, affect, behavior, and context. These areas encompass self-regulatory learning strategies that are conceptualized as potential mediators between personal characteristics (cognitive and non-cognitive) and performance (Pintrich, 2004). It should be noted that these personal characteristics might be individual differences in both cognitive and non-cognitive traits, which may play a role in the kind or functioning of the self-regulation strategies chosen by each student. For example, the executive function required for self-regulation is probably moderated by both cognition ability and personality traits such as conscientiousness. In short, these five SRL areas can be subsumed under the three areas of psychological functioning (Hilgard, 1980): cognition, motivation, and affect. Given that motivation and affect belong to the non-cognitive area, for the sake of parsimony, in this study we organized the self-regulatory learning strategies identified by Pintrich et al., (1991; Pintrich, 2004) and assessed by the MSLQ into the greater categories of cognitive and non-cognitive domains.

The cognitive domain consists of cognitive learning strategies (i.e., rehearsal, elaboration, organization, and critical thinking and metacognitive learning strategies). The non-cognitive domain covers the regulation of motivation, affect, behavior and context (MABC) described by Pintrich (2004), including time and study environment regulation, effort regulation, peer learning, and help-seeking. SRL strategies have been shown to display weak-to-moderate associations to AP, with the strongest associations being with effort regulation, time, study environment, and metacognitive self-regulation (Credé & Phillips, 2011).

Our integrative framework (see Table 1) summarizes these taxonomies and provides a tentative solution to the lack of a comprehensive theoretical framework of the potential predictors of AP. Following previous recommendations (Azevedo, 2020; Jensen, 1989; De Raad & Schouwenburg, 1996; Thomas et al., 2017), our proposed framework incorporates a set of the main predictors recently identified by Richardson et al., (2012) and organizes them bringing together two approaches: individual differences and SRL. Both these branches cross the five self-regulatory learning areas (Pintrich, 2004), the three traditional areas of psychological functioning (Hilgard, 1980), and the two broad domains of individual differences: intelligence and cognitive abilities as cognitive factors; and personality traits, motivation, and affect/mood as non-cognitive factors (Borghans et al., 2008; Chamorro-Premuzic, 2007; Cooper, 2010; Heckman & Rubinstein, 2001; Siegling & Petrides, 2016). While we recognize that there is no consensus on how to reconcile these different classifications of variables, Table 1 is intended to provide a parsimonious grouping consistent enough to serve as a starting point for future integrative models of SRL and individual differences approaches.

Table 1 Psychological Predictors of Academic Performance from SRL and Individual Differences Approaches

Human Capital factors[a]	*Areas of psychological functioning*[b]	*Individual differences main predictors*[c]	*Areas for self-regulation of learning*[d]	*Social-cognitive main predictors*[c]
Cognitive Factors	Cognition	Cognitive abilities (e.g., **fluid intelligence**, crystallized intelligence, working memory, **previous academic performance**)	Cognition	Cognitive & meta-cognitive learning strategies (e.g., **rehearsal, elaboration, organization, critical thinking, metacognition**)
Non-cognitive Factors	Motivation	Personality (e.g., **Conscientiousness**, Grit, Procrastination)	Motivation	Control Beliefs Expectancy (e.g., Academic self-concept, **Academic self-efficacy**, Performance self-efficacy, Self-handicapping, **AE Absorption**) Task value (e.g., **AE Dedication**, Intrinsic Goals, Extrinsic Goals)
	Affect	Emotional Intelligence (Ability EI, **Trait EI**)	Affect	**AE Vigour** Task anxiety Achievement emotions
			Behaviour	**Effort regulation** Help-Seeking
			Context	**Time and study environment** Peer learning

Note. Variables measured in this study are depicted in boldface. AE = Academic Engagement; EI = Emotional Intelligence

[a]According to Heckman & Kautz (2012) and Weschler (1943); [b] According to Hilgard (1980); [c] Adapted from Richardson et al., (2012); [d] According to Pintrich (2004)

Research Aims and Hypotheses

Unfortunately, most research exploring psychological predictors of university AP focuses exclusively on one area of psychological functioning as well as on one approach, studying just a handful of predictors. Although theoretical efforts examining some permutations of predictors exist (e.g., Sanchez-Ruiz et al., 2016; Chen et al., 2000), to our knowledge, no previous empirical work has met this long-standing target in university settings across a three-year long degree, which can provide comprehensive data on the long-term effects predictors.

Therefore, the first aim of this study is to explore the viability of our proposed integrative framework in explaining the combined influence of selected cognitive and non-cognitive factors, with special interest in testing the incremental validity of the latter in the prediction of AP over and above the traditional cognitive factors. Specifically, we put forth the following hypotheses:

H1a. Conscientiousness, academic engagement, academic self-efficacy and the MSLQ Factor 2, as the joint operationalization of the regulation of motivation, affect, behaviour and context (see Table 1), will predict AP throughout the 3-year period of undergraduate studies.

H1b. The previous non-cognitive factors will remain as significant predictors of AP in the presence of cognitive factors (i.e., cognitive ability, previous AP, cognitive SRL strategies measured by MSLQ Factor 1) throughout the 3-year period of undergraduate studies.

The second aim is to identify a reduced set of core non-cognitive factors with robust criterion validity. Following the preceding arguments and taking into account the non-cognitive areas for self-regulation of learning (regulation of motivation, affect, behavior, and context) identified by Pintrich (2004), and based on some of the most robust correlates of AP (i.e., those with an average $r > .20$) in the meta-analysis by Richardson et al., (2012), we expect to identify a valid structural equation model (SEM) and test the criterion validity of a global proxy of non-cognitive factors (i.e., a latent multifaceted non-cognitive factor) in the prediction of a latent university GPA factor. To this end, we set out our second hypothesis as follows:

H2. A latent global proxy of the non-cognitive factors (conscientiousness, academic engagement, academic self-efficacy and the MSLQ Factor 2) will significantly predict a latent factor of AP throughout three years of university degree.

Method

Participants

The convenience sample consisted of 386 Spanish undergraduate students (291 female) ranging in age between 17 and 46 years ($M = 21.05$; $SD = 4.85$). Participants were enrolled in a 3-year degree in Education at the University of Lleida, which is a public institution in Spain.

Measures

Academic performance (AP)

Official records were used as objective indicators of previous AP and the criterion variable, university AP. University students' grade point average (GPA) score was used as a measure of university AP. It was obtained within three years of the degree program, at three separate time points, at the end of each academic year: GPA year 1, GPA year 2, GPA year 3. The interest in taking three different indicators of GPA rests on the assumption that the nature of the classes taken during a given year might demand different sets of non-cognitive skills than those demanded in another year, thus allowing for potential differences in the relationship of the predictors to the criterion to be observed.

Each year students took approximately 60 credits and an average of 10 different subjects per year. In order to make students' average grades comparable with each other, the GPA score for each year was calculated for each student by weighting their average grade according to the ratio of enrolled credits over maximum credits for the year. The possible range of non-standardised GPA scores was from 0 to 3, but the actual range was from 0.12 to 2.88, with the average GPA for each year being progressively increasing from GPA first year = 1.45 ($SD = 0.51$) to GPA second year (t (228) = 6.52; $p < .001$), as well as from GPA second year = 1.58 ($SD = 0.52$) to GPA third year = 1.74 ($SD = 0.54$) (t (228) = 10.63; $p < .001$). Most of the students completed the degree, since only 8 students dropped out of the degree.

Concerning previous AP, it was a composite calculated with 60% being the cumulative GPA obtained in high school and 40% being the score on the Spanish university entry examination (knowledge-based test), called ‘Selectividad’ or "Prueba de Acceso ala Universidad"(i.e., University entrance exam). All achievement scores were previously standardized to be combined in the resulting prior AP scores.

Cognitive ability (Fluid Intelligence)

The Primary Mental Abilities test - Factor R ‘Reasoning’ (PMA-R; Thurstone & Thurstone 1962) is considered a good indicator of inductive reasoning, which entails the identification of new relationships in patterns by inferring the rules (e.g., Hertzog & Bleckley 2001). Inductive reasoning is a first-order factor in the hierarchical structure of cognitive ability located under Gf (fluid intelligence; Carroll 2014). The PMA-R involves a series of letters in a particular pattern and is asked to identify the next letter based on the pattern. The PMA-R was used as a proxy of Gf, in line with previous studies (e.g., Cejudo et al., 2017; Chamorro-Premuzic et al., 2009). In this study, this measure displayed good internal consistency (MacDonald’s total omega, $\omega = 0.85$).

Personality

The Goldberg’s Bipolar Adjectives - Short Form (GBA-SF; Goldberg 1992; Spanish adaptation by García et al., 2004) is a 25-item questionnaire that assesses five personality dimensions corresponding to the Big Five personality traits (e.g., Sanchez-Ruiz et al., 2011): extraversion, agreeableness, conscientiousness, emotional stability (low neuroticism), and openness. Each item consists of a pair of bipolar personality traits reflecting one dimension and is rated on a 9-point Likert scale ranging from 1 (*very* [*pole A of the trait*]) to 9 (*very* [*pole B*]). This questionnaire has shown strong correlations with the NEO Five Factor Inventory (NEO-FFI; García et al., 2004). In this study, subscale internal consistencies were acceptable to good (MacDonald’s total omega, for openness $\omega = 0.78$, conscientiousness $\omega = 0.85$, extraversion $\omega = 0.90$, agreeableness $\omega = 0.71$, and emotional stability $\omega = 0.84$).

Trait EI

The Trait Emotional Intelligence Questionnaire (TEIQue v. 1.50; Petrides 2009; Spanish adaptation by Pérez-González 2010) is a 153-item questionnaire used to assess global (total) trait EI as well as 15 facets of EI reflecting four factors: wellbeing, emotionality, sociability, and self-control. A 7-point Likert scale was used ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). There is well-founded evidence on the criterion and incremental validity of the Spanish version of the TEIQue long form (Petrides et al., 2007a) and on the soundness of its psychometric properties (e.g., Pérez-González & Sanchez-Ruiz 2014). In this study, the internal consistency of the global score was satisfactory (MacDonald’s total omega, $\omega = 0.89$). The validity evidence for the global score of trait EI is very sound (Andrei et al., 2016).

Academic self-efficacy

Academic self-efficacy was assessed via four items developed for this study. The items were based on an established measure, the Academic Self-Efficacy Scale (ASE; McIlroy, 2000) (i.e., “My performance is good in the majority of the courses”, “I study hard”, “I know I will obtain good grades during my academic career”, “I am able to organize my study time well according to the requirements of each subject”). A 5-point Likert scale was used ranging from 1 (totally disagree) to 5 (totally agree). The internal consistency of the composite score was acceptable (MacDonald’s total omega, $\omega = 0.70$).

Academic Engagement

The Student Academic Engagement scale (SAE; Spanish version; Schaufeli et al., 2002b) is a 17-item questionnaire assessing three dimensions of academic engagement: vigor, dedication, and absorption. A 7-point Likert scale was used ranging from 0 (*never*) to 6 (*always or every day*). Internal consistencies were good in this study (MacDonald’s total omega for global, $\omega = 0.92$, vigor $= 0.84$, dedication $= 0.80$, and absorption $= 0.78$).

Self-regulated learning strategies

The Learning Strategies subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991; Spanish version; Roces et al., 1995) was used to assess students’ use of learning strategies (50 items) through a 7-point Likert scale ranging from 1 (*not at all true of me*) to 7 (*very true of me*). This construct encompasses nine subscales: students’ cognitive learning strategies (i.e., rehearsal, elaboration, organization, and critical thinking), metacognitive learning strategies (i.e., ability to adaptively regulate one’s mental processes), and management of resources available for studying (i.e., time and study environment regulation, effort regulation, peer learning, and help-seeking). The partial use of this instrument is common in the literature (e.g., Kickert et al., 2019; Suárez Riveiro et al., 2001).

For the purposes of the set of hierarchical regressions, which required the extraction of a smaller number of factors for analysis, an exploratory factor analysis (EFA) was conducted on subscales (Bernstein & Teng, 1989). Likewise, despite the MSLQ is a well-known instrument, there is unsatisfactory evidence for the hypothesized structures given the scarcity of measurement work that examines the entire latent factor structure of the instrument has been highlighted as an important gap in the MSLQ literature (e.g., Cho & Summers 2012; Hilpert et al., 2013). Using principal axis extraction and oblimin/promax rotations from the nine subscales, Horn’s (1965) parallel analysis indicated a two-factor solution. The two factors explained 51% of the variance, tapping into ‘Regulation of cognition and metacognition’ (Factor 1) and ‘Regulation of behavior and context’ (Factor 2). Factor 1 showed good internal consistency (MacDonald’s total omega, $\omega = 0.84$) and included elaboration, organization, and critical thinking and the metacognitive self-regulation subscales. Factor 1 may indicate the ‘Deep’ student approach to learning (SAL) according to Pintrich (2004). Factor 2 was also reliable (MacDonald’s total omega, $\omega = 0.72$) and included the rehearsal subscale (related to ‘Surface’ SAL; Pintrich 2004) and the time and study environment and effort regulation subscales. Help-seeking and peer-learning subscales did not significantly load on any factor, so they were excluded in further analyses.

Procedure

The study was approved by the university's institutional review board. The questionnaires were administered as hard copies by the researchers and trained university staff at the beginning of the participants' degree in a classroom setting. The length of the testing session ranged between 50 and 75 min. Participants had a 10-minute break after 45 min. Students' participation was voluntary and was not part of an assignment. Participants received no incentives for their participation.

Statistical analyses

Correlations and hierarchical regressions

Intercorrelations between all the study variables were conducted. Three two-step hierarchical regressions were run, one for each university year with its respective GPA score as the outcome and cognitive and non-cognitive variables as predictors, at step 1 and 2, respectively.

Structural equation models (SEMs)

In order to find a sample size sufficient to minimize Type II error, a power analysis was performed using WebPower (Zhang & Yuan, 2018; https://webpower.psychstat.org/wiki/) following the recommendations by MacCallum et al., (1996). The parameters established for the calculation of the appropriate sample size were: 320 degrees of freedom, taking a RMSEA of 0.06 over the Null Hypothesized RMSEA of 0.05, a significance level at 0.05, and a power goal of 0.80. The resulting required sample size was 300 participants. Therefore, the final power for our study with 386 students exceeded the expectations (0.90).

Two SEMs were tested combining measures representing the shared variance among each of the areas of regulation of learning (Pintrich, 2004; see Table 1). Concerning the criterion variable, a latent university GPA variable was constituted from the shared variance among the manifest GPA year 1, GPA year 2 and GPA year 3.

Results

Correlations

Bivariate correlations among the key study variables are presented in Table 2. Bonferroni correction was applied to reduce Type I error rate. After applying Bonferroni correction, only p values less than 0,00022 were considered significant (depicted in bold in Table 2). First year university GPA showed the strongest correlation with previous AP ($r = .51$, $p < .00022$), followed by academic self-efficacy ($r=.42$, $p<.00022$), academic engagement ($r=.38$, $p<.00022$), MSLQ's factor 2 ($r=.37$, $p<.00022$), MSLQ's factor 1 ($r=.32$, $p<.00022$), and conscientiousness ($r=.30$, $p<.00022$).

Second year university GPA showed the strongest correlation with previous AP ($r=.63$, $p<.00022$), followed by academic self-efficacy ($r=.48$, $p<.00022$), MSLQ's factor 2 ($r=.41$, $p<.00022$), academic engagement ($r=.41$, $p<.00022$) and MSLQ's factor 1 ($r=.41$, $p<.00022$), and conscientiousness ($r=.28$, $p<.00022$).

Third year university GPA had the strongest correlation with previous AP ($r=.63$, $p<.00022$), followed by academic self-efficacy ($r=.43$, $p<.00022$), academic engagement ($r=.40$, $p<.00022$), MSLQ's factor 2 ($r=.38$, $p<.00022$), MSLQ's factor 1 ($r=.32$, $p<.00022$), and conscientiousness ($r=.25$, $p<.00022$). In addition, the GPA scores for year 1st, 2nd and 3rd were highly intercorrelated ($r=.80$-0.95, $p<.00022$).

Hierarchical regressions

No multicollinearity problems were observed since tolerance values were >0.20 and VIF was <4.00 in all steps. The subject-to-predictor ratio is over 10:1. Three separate analyses were carried out with GPA as the criterion for each of the three academic years (see Table 3). We have followed two steps, first introducing the short set of selected non-cognitive predictors. In the second step we added the selected cognitive predictors, in order to see which variables from the first step still showed predictive validity. After applying Bonferroni correction, only p values less than 0,012 were considered significant in Step 1, and only p values less than 0,007 were considered significant in Step 2.

Using first year GPA as the criterion variable, at step 1, the three non-cognitive variables were significant predictors ($F(4, 184)=16.94$, $p<.001$, adjusted $R^2=0.25$): academic engagement ($\beta=0.21$, $p<.01$), academic self-efficacy ($\beta=0.21$, $p<.05$) and regulation of behavior and context (MSLQ Factor 2) ($\beta=0.22$, $p<.05$). In the second step ($F(7, 181)=23.54$, $p<.001$, adjusted $R^2=0.46$), the only significant cognitive predictor was previous AP ($\beta=0.52$, $p<.001$), while two non-cognitive predictors were significant: academic engagement ($\beta=0.20$, $p<.01$) and regulation of behavior and context (MSLQ Factor 2) ($\beta=0.21$, $p<.01$). The ΔR^2 was significant from step 1 to 2.

Using second year GPA as the criterion variable, at step 1, two out of the three non-cognitive variables were significant predictors ($F(4, 179)=14.15$, $p<.001$, adjusted $R^2=0.22$): academic self-efficacy ($\beta=0.27$, $p<.01$) and regulation of behavior and context (MSLQ Factor 2; $\beta=0.23$, $p<.01$). However, the p values did not reach significance after Bonferroni correction. In the second step ($F(7, 176)=26.69$, $p<.001$, adjusted $R^2=0.50$), the only significant cognitive predictor was previous AP ($\beta=0.60$, $p<.001$), while only significant non-cognitive predictor was regulation of behavior and context (MSLQ Factor 2) ($\beta=0.21$, $p<.01$). The ΔR^2 was significant from step 1 to 2.

Using third year GPA as the criterion variable, at step 1, the three non-cognitive variables were significant predictors ($F(4, 175)=10.19$, $p<.001$, adjusted $R^2=0.17$): academic engagement ($\beta=0.17$, $p<.05$), academic self-efficacy ($\beta=0.20$, $p<.05$) and regulation of behavior and context (MSLQ Factor 2) ($\beta=0.19$, $p<.05$). In the second step ($F(7, 172)=21.17$, $p<.001$, adjusted $R^2=0.44$), the only significant cognitive predictor was previous AP ($\beta=0.59$, $p<.001$), while two non-cognitive predictors were significant: academic

Table 2 Correlations with Pre-university and University Academic Performance

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Previous AP	—														
2. 1st Year GPA	**0.51*****	—													
3. 2nd Year GPA	**0.63*****	**0.88*****	—												
4. 3rd Year GPA	**0.63*****	**0.80*****	**0.95*****	—											
5. Inductive reasoning	0.06	−0.10	−0.08	−0.10	—										
6. Openness	0.05	0.06	0.05	0.06	0.04	—									
7. Conscientiousness	**0.23*****	**0.30*****	**0.28*****	**0.25*****	−0.05	0.11	—								
8. Extraversion	−0.06	−0.02	−0.02	0.01	−0.02	**0.37*****	0.04	—							
9. Agreeableness	−0.05	0.06	0.02	0.02	0.04	**0.35*****	**0.31*****	**0.46*****	—						
10. Emotional stability	−0.11	−0.05	−0.04	−0.01	−0.01	**0.22*****	**0.21*****	**0.08**	**0.26*****	—					
11. Trait EI	0.02	0.08	0.06	0.08	−0.01	**0.34*****	**0.32*****	**0.41*****	**0.39*****	**0.51*****	—				
12. Academic Engagement	**0.24*****	**0.38*****	**0.41*****	**0.40*****	−0.15**	0.11	**0.43*****	0.19**	0.17**	0.06	**0.39*****	—			
13. Academic Self-efficacy	**0.39*****	**0.42*****	**0.48*****	**0.43*****	−0.06	0.12*	**0.47*****	0.15**	0.16**	0.09	**0.28*****	**0.54*****	—		
14. MSLQ Factor 1	**0.24*****	**0.32*****	**0.34*****	**0.32*****	−0.08	**0.24*****	**0.26*****	0.20***	0.15**	0.02	**0.31*****	**0.48*****	**0.43*****	—	
15. MSLQ Factor 2	**0.30*****	**0.37*****	**0.41*****	**0.38*****	−0.03	0.05	**0.51*****	0.10	0.15**	−0.05	0.17**	**0.54*****	**0.60*****	**0.49*****	—

Note. Previous AP = Previous Academic Performance as Entry score; GPA = Grade Point Average; EI: Emotional Intelligence; MSLQ Factor 1 = MSLQ factor for Regulation of Cognition and Metacognition; MSLQ Factor 2 = MSLQ factor for Regulation of Behavior and Context

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .00022$. After applying Bonferroni correction, only p values less than 0,00022 were considered significant (in bold)

Table 3 Hierarchical Regression Predicting GPA from Non-cognitive (Step 1) and Cognitive (Step 2) Predictors

		1st Year GPA		2nd Year GPA		3rd Year GPA	
Model	Predictor	*β*	*t*	*β*	*t*	*β*	*t*
Step 1	Conscientiousness	-0.04	-0.61	-0.02	-0.21	-0.07	-0.92
	AEngagement	0.21	2.67**	0.08	0.94	0.17	1.97*
	ASelf-efficacy	0.21	2.47*	0.27	3.05**	0.20	2.16*
	MSLQ Factor 2	0.22	2.61*	0.23	2.71**	0.19	2.07*
	F/ Adj. R^2	16.94/ **0.25*** **		14.15/ 0.22**		10.19/ **0.17*** **	
Step 2	Conscientiousness	-0.08	-1.23	-0.06	−0.88	-0.11	-1.69
	AEngagement	0.20	2.84**	0.08	1.14	0.16	2.01*
	ASelf-efficacy	-0.02	-0.20	0.00	0.02	-0.06	-0.76
	MSLQ Factor 2	0.21	2.79**	0.21	2.88**	0.16	2.05*
	Previous AP	0.52	8.35***	0.60	9.10***	0.59	9.21***
	Inductive reasoning	-0.11	-1.95	−0.07	-1.30	-0.10	-1.71
	MSLQ Factor 1	0.01	0.18	0.04	0.66	0.07	1.07
	F/Adj. R^2	23.54/ **0.46*** **		26.69/ **0.50*** **		21.17/ **0.44*** **	
	Δ F/Δ R^2	23.89/ 0.21***		33.23/0.27***		29.24/ 0.27***	

Note. GPA = Grade Point Average; Previous AP = Previous Academic Performance as Entry score; MSLQ Factor 1 = MSLQ factor for Regulation of Cognition and Metacognition; MSLQ Factor 2 = MSLQ factor for Regulation of Behavior and Context. Significant Adj. R^2 is highlighted in boldface

* $p<.05$, ** $p<.01$, *** $p<.001$. After applying Bonferroni correction, only *p* values less than 0,012 were considered significant in Step 1, and only *p* values less than 0,007 were considered significant in Step 2

engagement ($\beta=0.16$, $p<.05$) and regulation of behavior and context (MSLQ Factor 2) ($\beta=0.16$, $p<.05$). The Δ R^2 was significant from step 1 to 2.

Structural equation models (SEMs)

A structural equation model was set up in AMOS, whereby a latent predictor factor was modeled as an exogenous variable and university GPA across three years as an endogenous variable. We explored statistics of skewness and kurtosis as indicators of normality. The absolute values of the minimum and maximum skewness and kurtosis were 0.06 and 0.79, which were well within the limits of past research recommendations: skewness < 2, kurtosis < 7 (Curran et al., 1996). Since data were relatively normally distributed, we tested two SEM models with maximum likelihood estimation (see Figs. 1 and 2 for a depiction of the models, respectively; see Table 4 for a summary of fit results for the SEMs).

The first model is a theory-driven proposed model. In the first model, a comprehensive latent variable of non-cognitive predictor reflecting regulation of Motivation, Affect, Behavior, and Context (MABC) was operationalized via next manifest variables: academic engagement, academic self-efficacy, conscientiousness, and MSLQ's factor 2. This latent variable was regressed onto the same latent GPA factor representing the shared variance among the manifest GPAs from the first, second, and third year of the degree. Figure 1 depicts the resultant standardized estimates. This Model 1 (or MABC model) resulted in good fit to the

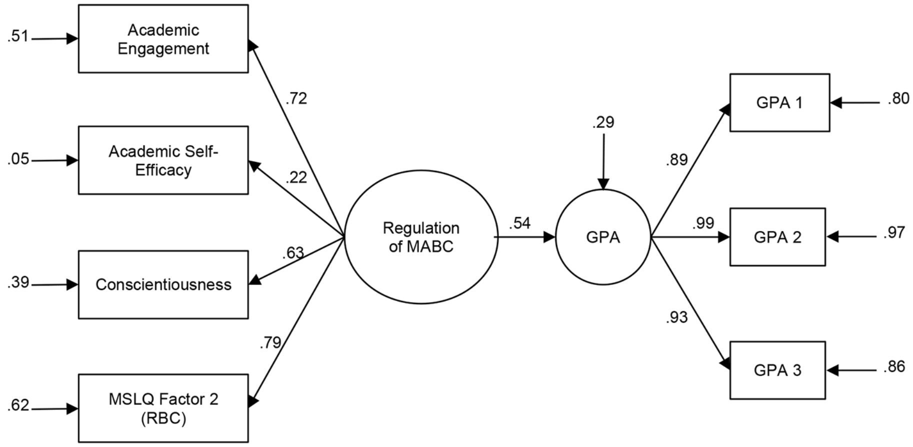

Fig. 1 *Structural Model 1 Predicting 3-Years GPA from Latent Regulation of Motivation, Affect, Behavior, and Context factor (MABC) as a Non-Cognitive Predictor*
Note. Standardized maximum likelihood parameters are shown. RBC = Regulation of Behavior and Context (MSLQ Factor 2).

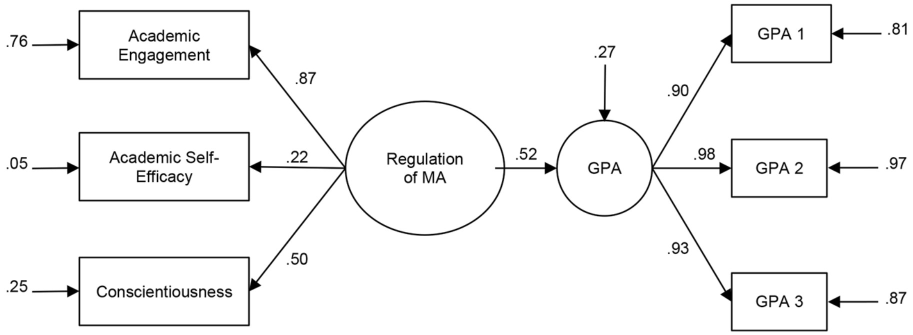

Fig. 2 Structural Model 2 Predicting 3-Years GPA from Latent Regulation of Motivation and Affect factor (MA) as a Non-Cognitive Predictor
Note. Standardized maximum likelihood parameters are shown.

data according to cut off criteria by Hooper et al., (2008), except for the parsimony index, $\chi^2(14)=39.555$, $p<.001$, TLI=0.950, RMSEA=0.069, CFI=0.975, PCFI=0.488. The TLI, an index that prefers simpler models (Hooper et al., 2008), was acceptable but suggested room for improvement.

The second model is partially a data-driven model, based on the above model, so that it is a modified model 1. This second model was conducted in order to explore the possibility for improvement of model 1 in terms of both TLI and parsimony (PCFI). In this second model, the regulation of Behavior and Context was omitted, so that a narrower latent variable of non-cognitive predictor reflecting regulation of Motivation and Affect (MA) was operationalized via next manifest variables: academic engagement, academic self-efficacy, and conscientiousness. This latent variable was regressed onto the same latent GPA factor

Table 4 Summary of Fit Results for the Structural Models

Type of Fit Index	Index	Cutoff Criteria[a]	Model 1	Model 2
Absolute	χ^2 /df	2.00–5.00	2.825	2.783
	RMSEA	<0.08	0.069	0.068
Relative	TLI	≥0.95	0.950	0.956
	CFI	≥0.95	0.975	0.981
Parsimony	PCFI	>0.50	**0.488**	**0.421**

Note. n=386; df=degrees of freedom; RMSEA=Root mean square error of approximation; TLI=Tucker-Lewis Index=NNFI (Non-Normed Fit Index); CFI=Comparative fitness index; PCFI=Parsimony CFI

[a] Based on Hooper et al., (2008). Indices under acceptable threshold levels are in boldface

representing the shared variance among the manifest GPAs from the first, second, and third year of the degree. Figure 2 depicts the resultant standardized estimates. This Model 2 (or MA model) resulted in good fit to the data, except for the parsimony index, $\chi^2(9)=25.047$, $p=.003$, TLI=0.956, RMSEA=0.068, CFI=0.981, PCFI=0.421. Except for parsimony (PCFI), all the indices improved slightly with this model with respect to Model 1.

In sum, Model 1 showed greater explanatory power (29% of the variance) vs. Model 2 (27% of the variance), as well as slightly higher level of parsimony (Model 1's PCFI=0.49 vs. Model 2's PCFI=0.42).

Discussion

The present exploratory study aimed to identify core non-cognitive predictors of AP and their differential significance as a first step to build an integrative model to predict AP in higher education.

Results confirmed previous AP to be the strongest predictor of university GPA, supporting the premise of this study in line with previous research (Richardson et al., 2012). Surprisingly, contrary to most of the previous investigations into individual differences, cognitive ability displayed no significant association with AP in any of the analyses. Nevertheless, non-significant or weak correlations have been previously reported (e.g., Chamorro-Premuzic et al., 2009; Mavroveli & Sanchez-Ruiz, 2011) between intelligence and AP. Specifically, also using a sample of Spanish undergraduate students, Chamorro-Premuzic et al., (2009) found a non-significant correlation between fluid intelligence and previous AP in terms of university entry examinations, which is a quite similar result to the correlation we found.

Regarding non-cognitive factors, academic self-efficacy, academic engagement, conscientiousness, and non-cognitive SRL strategies were strongly associated with AP. Our results indicate that it is possible to explain a quarter of the variance in university GPA from a reduced set of non-cognitive variables alone, in accordance with the conclusions of Heckman and colleagues (e.g., Heckman & Kautz 2012).

Through hierarchical regressions, up to about 25% of the variance in university GPA scores can be accounted for only by non-cognitive factors such as academic engagement (a proxy of regulation of motivation and affect) and strategies for the regulation of behavior and context, thus showing support for H1a. As expected in H1b, with the addition of previous AP as cognitive predictor, up to about 50% of the variance in university GPA was explained. Conscientiousness was confirmed as a distal robust correlate of GPA scores, but in the hierarchical regressions it loses predictive capacity in the presence of other proximal motivational constructs such as academic engagement, academic self-efficacy and regulation of behavior and context (MSLQ factor 2). However, although there was empirical overlap between conscientiousness and these other three variables, the overlap was not problematic, therefore the variables can still capture the individual differences in optimal personal qualities (Pintrich & Zusho, 2007) for the efficient regulation of motivation in learning.

These findings have important implications on the significance of personality traits such as conscientiousness in relation to academic achievement. According to the findings of the present study, those students who believe in their capabilities, are making deliberate efforts in their academic endeavors, are showing responsibility, and are using SRL strategies were more academically successful. To go further, the findings of the present study can imbue professionals in education who are able to implement strategies that foster the development of behaviors associated with these non-cognitive factors, focusing on counseling and training for the improvement of the regulation of motivation, affect, behavior and context. Additionally, these findings can inform interventions that target students who are facing academic difficulties (McKenzie & Schweitzer, 2001).

Additionally, the SEMs were carried out with statistical power guarantees and represented a good fit to the data. The SEMs explained about 30% of the variance in university GPA with only a reduced set of 3–4 non-cognitive factors as combined predictors, thus supporting the robust criterion validity of non-cognitive factors or soft skills, as advocated by Heckman & Kautz (2012). Focusing on fit results, RMSEA, TLI and CFI slightly preferred Model 2 while PCFI preferred Model 1 (although PCFI still indicates acceptable but not good parsimony in both cases). Nonetheless, considering that Model 1 is the theory-based model derived from the literature (H2), and both power of variance explained, and level of parsimony are higher, it seems pertinent to recommend that Model 1 be subjected to replication studies in the future. Thus, H2 was fully supported by the results obtained through SEM.

In our theory-based proposed model 1, non-cognitive factors were operationalised as a latent factor capturing the variance shared between academic engagement, academic self-efficacy, regulation of behavior and context, and conscientiousness. Both hierarchical regression and SEMs findings have demonstrated the remarkable predictive validity of these four non-cognitive factors. Furthermore, it is worth noting that step 2 in the hierarchical regressions has revealed the unique incremental validity of academic engagement and regulation of behavior and context (MSLQ Factor 2) over and above cognitive variables such as previous AP, inductive reasoning and regulation of cognition and metacognition, which constitutes hard evidence in favor of soft skills, thus extending the work by James Heckman and colleagues (Borghans et al., 2001; Heckman & Kautz 2012).

These novel findings support the role of non-cognitive factors in university AP, as well as our theoretical integrative model of psychological predictors as a framework for the design of new empirical studies. The pattern of results suggested the possible presence of a mediator effect in the relation between conscientiousness and AP. This is in line with the widespread assumption that distal predictors affect AP via proximal processes (Chen et al., 2000; Conrad & Patry, 2012). To some extent, motivation can be conceptualized in terms of personality traits such as conscientiousness, which is closely related to effort regulation (Chamorro-Premuzic & Furnham, 2003) and has been referred to as the "will to achieve" (Digman, 1989). Hence, the role of conscientiousness as a predictor of AP is defined by a propensity to effortful and ambitious achievement-striving (Chamorro-Premuzic et al., 2009), which may be better captured through self-reports of proximal and situational variables (e.g., academic self-efficacy). Perhaps for this reason the significant effect of conscientiousness as a predictor of AP disappeared in the presence of these self-reports in our hierarchical regressions. However, this is rather speculative and remains to be explored by further studies.

Contrary to previous findings (e.g., MacCann et al., 2020; Sanchez-Ruiz et al., 2013) trait EI showed no significant association to AP in either of the analyses, although it significantly correlated with academic engagement, SRL strategies, and academic self-efficacy. It should be considered that many studies, including the meta-analyses by MacCann et al., (2020) and Perera & DiGiacomo (2013), reported weak to moderate correlations between trait EI and AP (Petrides et al., 2018; Perera & DiGiacomo, 2013) and also reported moderating effects of academic level and age, whereby the relationship between trait EI and AP was weaker at the university level compared to primary school. Nevertheless, the findings of the present study may be also explained by the indirect effects of trait EI on AP. Specifically, emotional self-efficacy, an important aspect of trait EI, is likely to influence many factors that impact AP (Petrides et al., 2018; Qualter et al., 2012). For instance, emotional self-efficacy has been shown to positively impact academic self-efficacy, leading to enhanced AP (Adeyemo, 2007; Hen & Goroshit, 2014). Additionally, emotional self-efficacy may influence the self-regulatory strategies chosen for various educational activities and one's emotional response to academic stressors (Bandura, 1999; Bandura, 2001; Qualter et al., 2012). The latter is due to how one's beliefs regarding his or her emotional response in past academic settings can influence the responses in the future (Parsons & Ruble, 1977; Qualter et al., 2012).

Regulation of behavior and context (factor 2 of MSLQ) explained additional variance in AP over and above cognitive variables like previous AP. However, the rehearsal, time and study management, and effort regulation subscales were previously found to have small to moderate correlations with university GPA (Richardson et al., 2012). In addition, academic self-efficacy had the highest correlation with AP following previous AP, supporting previous research (e.g., Lee et al., 2014). Furthermore, this may give insight into research pointing to the role of self-efficacy in academic motivation (e.g., Schunk 1991) and self-motivated academic goal setting (Zimmerman et al., 1992). This may also suggest a pathway of influence where previous AP enhances academic self-efficacy which, in turn, influences AP, in line with Bandura's (1977) suggestion. Our study has focused on quantifying the joint predictive power of individual dispositional differences along with SRL on AP. As we have noted earlier, cognitive and non-cognitive factors, such as conscientiousness and academic engagement, may influence the SRL cycle in both Printich's and Zimmerman's model. Future studies could build on our findings by investigating the differential impact of such factors in each of the phases of the SRL process.

Concerning the SEMs, where the predictor variable was conceived as a latent factor composed by the shared variance of several non-cognitive factors, both Model 1 and Model 2 showed good fit to the data as well as very similar size effects, but the Model 1 was somewhat more parsimonious, as well as more comprehensive and slightly higher in predictive validity. This is the first time, to our knowledge, that a proxy of a general variable of non-cognitive factors is generated through structural equation modeling and its criterion validity on university GPA is successfully tested, extending the work by Heckman and colleagues with a sample coming from a non-English speaking country (i.e., Spain) and a specific major (i.e., Teachers Education College).

Our contribution is threefold: first, for having integrated multiple predictors from the SRL perspective and from the perspective of individual differences, filling the gap noticed by Azevedo (2020), Jensen (1989) or De Raad & Schouwenburg (1996); second, for having verified, in a non-Anglo-Saxon country, the combined and separate predictive power of the main variables identified in the meta-analysis by Richardson et al., (2012); and, third, for having demonstrated for the first time that a general latent factor of non-cognitive factors formed from variables from the two research traditions can evidence criterion validity on the university GPA recorded over three subsequent years, as suggested by econometric analyses by the Nobel laureate James Heckman.

Limitations and future directions

Strengths of the present study include its comprehensive approach integrating cognitive and non-cognitive aspects to predict AP across years of study, which significantly contributes to the scarce literature with the same purpose (e.g., Richardson et al., 2012). Nevertheless, this study has several limitations. First, concerning the method, although the sample is overwhelmingly female, this is representative of the Spanish education sector whereby around 70% of education professionals (Instituto Nacional de Estadística, 2020) and 77.5% of undergraduate students in education degrees are female (Corporación de Radio y Televisión Española, 2019). Second, the length of the data collection session may be considered a limitation as it may have fatigued the participants and so biased the results, although, as explained above, participants were given the opportunity to take a 10-minute break after 45 min. Third, although research in this area has consistently used GPA to indicate AP (Richardson et al., 2012) since GPA has been found to be internally consistent (Bacon & Bean, 2006) and reliable over time (Schuler et al., 1990), future research should attempt to adjust for potential statistical artifacts such as grade inflation (e.g., Johnson 2006) that can undermine the strength of observed correlations with GPA (Poropat, 2009). Fourth, the non-significant findings of cognitive ability obtained in this study might be due to (a) the narrow assessment of the construct (Reeve et al., 2014), (b) the range restriction in intelligence scores among university students, and (c) the sample consisting of students pursuing the same degree (Sanchez-Ruiz et al., 2013). Thus, future research may benefit from recruiting a more diverse sample and adopting a multilevel analysis approach to predicting AP. Finally, even though we used an objective measure of AP as the outcome (official GPA records) and a maximum-performance test to measure cognitive ability (i.e., fluid intelligence via the PMA-R), the rest of predictors were assessed using self-report measures, which allows for the possibility of mono-method bias.

Additionally, the academic challenges and demands in high school and college may differ and this may be associated with changes in AP (Credé & Kuncel, 2008). However, in spite of this, the main non-cognitive predictors of AP in this study were relevant to both high school and college GPAs. In addition, even though our study measured a wide set of non-cognitive variables, additional ones may be worth exploring, such as, students' approaches to learning, study habits, study attitudes, and psychosocial contextual variables (e.g., academic majors). In the same vein, future research expanding on the role of moderators and mediators in the trait EI and AP relationship is required.

Finally, this study examined MSLQ subscales as static predictors of AP but not the context specificity embedded in these measures. Future research should consider the context in which these learning strategies are applied and measured and examine within-person variations across different majors (Credé & Phillips, 2011). Moreover, future studies can benefit from exploring trait EI in terms of separate factor scores (i.e., wellbeing, emotionality, sociability, and self-control) instead of one global score.

Conclusions

Our findings confirm the significance of both SRL and non-cognitive factors in predicting university GPA (e.g., Heckman & Kautz 2012; Mega et al., 2014; Richardson et al., 2012), as well as extends the empirical literature integrating the SRL approach and the individual differences approach as previously demanded by experienced researchers such as Azevedo (2020), Jensen (1989), and De Raad & Schouwenburg (1996), among others.

Our proposed theoretical framework summarized in Table 1 as well as our Structural Model 1 depicted in Fig. 1 can be a useful road map for counseling and assessing students in education, targeting interventions for students at risk of academic difficulties, and designing future research investigating how different cognitive and non-cognitive personal characteristics contribute to (moderating or mediating) each phase and subprocess of the SRL cycle.

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Code Availability Not applicable.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

Ethical Standards This research involved human subjects, who filled out an informed consent. All ethical documentation regarding the study is available upon request.

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