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*Research article*

# Emotional engagement in the association between motivational beliefs and achievement in secondary school physics

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**Abstract:** Motivational beliefs are closely related to academic achievement, yet the affective processes through which they are associated with performance remain insufficiently specified in science education, particularly in subject-specific learning contexts such as Physics. General Emotional Engagement (GEE) may represent a relevant affective pathway in this association; however, it has rarely been examined as an intervening variable in structural models. In this study, we examined whether GEE is statistically associated with the link between motivational beliefs and Physics achievement in upper-secondary education. An initial sample of 340 secondary-school students completed measures of self-efficacy, expectancy of success, task value, and class-related achievement emotions. Two structural equation models were estimated, with socioeconomic status, gender, academic year, and academic track included as covariates. In both models, motivational beliefs were positively associated with GEE, which was positively associated with course grades; the indirect associations through GEE and the direct associations with grades were statistically significant. Overall, the findings support the view that emotional engagement may help explain how motivational beliefs are associated with achievement in Physics classrooms. Moreover, the self-efficacy model showed better fit and greater parsimony than the expectancy–value model, suggesting that competence-related beliefs may be more closely aligned with Physics achievement during adolescence.

**Keywords:** emotional engagement, achievement emotions, self-efficacy, expectancy-value, physics education, secondary school

## 1. Introduction

Adolescence is a developmental period in which students consolidate academic competencies that shape subsequent educational and occupational pathways [1]. In Uruguay, upper-secondary Physics is especially relevant because it coincides with track choice and with later STEM-related pathways. Even modest differences in competence-related beliefs and motivation may translate into meaningful differences in grades and subsequent persistence in science-related domains [2–4]. In particular, the subject is often perceived as difficult and is associated with ambivalent or declining attitudes toward science among secondary students [5–7]. It is therefore important to clarify how motivational and emotional processes are related to Physics performance.

Within science education, motivational beliefs are generally assumed to shape achievement over time, but the affective processes linking them to subject-specific performance remain unclear. For that reason, examining how these beliefs are related to students' emotional experience in classroom activity is theoretically important. In the introduction, we first outline the theoretical links among motivational beliefs, achievement emotions, and engagement, then review the relevant empirical literature, identify the major gaps, and finally state the aims and contribution of this study.

### 1.1. Theoretical background: Expectancy–value theory and social cognitive theory

Expectancy–value theory posits that students' achievement outcomes are proximally shaped by their expectations of success and the value they assign to learning activities. Situated extensions of the theory further emphasize that these beliefs are formed within social and institutional contexts, which is especially relevant in differentiated upper-secondary settings; in this framework, expectancy-related beliefs and task value are theorized to support persistence, effort, and achievement, especially as students move into more specialized or tracked programs [8–12]. A parallel line of theorizing is provided by social cognitive theory, which identifies self-efficacy as a central belief in students' academic functioning [13,14]. Self-efficacy refers to students' perceived capability to meet domain-specific academic demands and is understood as a core mechanism shaping how they interpret tasks, regulate effort, and persist when difficulties arise [15]. These effects are especially relevant in Physics, where sustained practice is often required. Because self-efficacy is shaped by mastery experiences, modeling, social persuasion, and affective cues, even modest differences in perceived capability may accumulate into meaningful differences in performance [16]. Although expectancy of success and self-efficacy are related competence-relevant beliefs, they are conceptually distinct. Expectancy refers to a relatively outcome-focused prediction of how well one will perform on a specific upcoming task, whereas self-efficacy refers to a broader judgment of one's capability to organize and execute the actions required to meet domain-specific demands. This conceptual distinction is one reason the two frameworks are compared under parallel conditions in this study, rather than treated as interchangeable.

Control–value theory (CVT) provides a complementary framework for explaining how motivational appraisals give rise to discrete achievement emotions and, in turn, shape academic functioning. Motivational beliefs do not operate in an affect-neutral manner: They are systematically intertwined with students' academic emotions, which can either facilitate or hinder the translation of motivation into sustained engagement and achievement [17,18]. CVT proposes that emotions emerge from students' appraisals of control (e.g., competence and efficacy) and value (e.g., importance and utility), and that these emotions influence cognitive resources, engagement, strategy use, and performance [17]. From a CVT perspective, expectancy- and efficacy-related beliefs capture students' sense of control (i.e., "Can I handle this?"), while task value captures their sense of value (i.e., "Is this worth it?"). These appraisals are expected to configure students' emotional experiences during learning, which then shape the quality and sustainability of their engagement and achievement-related behaviors.

### 1.2. Conceptualizing emotional engagement as an affective pathway

Emotional engagement has been conceptualized as a central dimension of students' connection to learning, complementing behavioral and cognitive engagement [19]. Work further suggests that emotional engagement can be understood in terms of activation versus deactivation during learning, and that disengagement is not merely low engagement but a qualitatively distinct process [20]. Some higher-education studies have likewise modeled academic engagement as an intervening variable between motivational beliefs and performance [21].

However, the conceptual value of emotional engagement as a meaningful variable depends on how it is conceptualized and measured: If it is treated as an undifferentiated affective composite, it may blur important differences among emotions that stem from different appraisal patterns and may relate differently to students' functioning. A more precise approach is to conceptualize emotional engagement in terms of discrete class-related achievement emotions [22] and represent their shared variance in an integrated measurement model. Understood in this way, the General Emotional Engagement (GEE) construct used here differs from the broad emotional-engagement indices common in engagement research, which typically rely on a small set of global items (e.g., interest or enjoyment of school). Rather than treating emotional engagement as a single undifferentiated rating, we model it as the variance shared across eight discrete class-related achievement emotions that, within Control–Value Theory, arise from students' control and value appraisals [17]. A hierarchical (third-order) specification was adopted rather than a purely valence-based representation because, in this framework, achievement emotions are differentiated not only by valence but also by activation [17,22]; a single positive–negative dimension would therefore not fully capture their structure. We retained a higher-order rather than a bifactor representation because our primary interest was in the common affective involvement that these emotions share in the Physics classroom while enabling each emotion to retain its content. The third-order factor captures this shared affective involvement, the second-order factors capture broader positive and negative dimensions, and the first-order factors retain the discrete emotions. Standardized factor loadings and residual variances for both structural models are summarized in the Results, and the full hierarchical measurement structure is described in Supplementary Material 1.

From this perspective, emotional engagement can be understood as students' affective involvement in learning activities, reflected in a predominance of positive activating emotions and relatively low levels of negative emotions associated with withdrawal or disengagement tendencies [23]. Reviews converge with this account by showing that enjoyment is typically linked to adaptive motivational and self-regulatory processes, whereas boredom and hopelessness are linked to reduced effort and disengagement [24–26].

### 1.3. Motivation, engagement, and achievement: Expectancy–value beliefs and self-efficacy

Expectancy–value beliefs and self-efficacy have been consistently linked to sustained effort, engagement, and achievement, supporting the broader claim that motivational beliefs matter for academic functioning. Self-efficacy is reliably associated with more adaptive learning behaviors and higher achievement [21,27], and Latin American evidence likewise suggests that it is meaningfully tied to adolescents' school adjustment [28–30]. In parallel, research in science education has increasingly emphasized that motivation and emotions are jointly implicated in students' participation and achievement. For example, a large SEM study with Chilean and Spanish secondary students showed that motivational variables predicted boredom and enjoyment in science classes, and that these emotions in turn helped explain engagement toward science studies, supporting the view that affective classroom experience is not merely concomitant to motivation but part of the process through which it becomes educationally consequential [31]. Evidence also suggests that emotions may not simply accompany motivated learning, but may help explain how motivational beliefs are reflected in achievement. In a mathematics study, Butkienė et al. [32] found that positive classroom-related emotions consistently mediated the associations between several motivational beliefs and achievement, whereas negative emotions showed a more limited mediating role. Although that study was conducted in mathematics and within a broader expectancy–value framework, it still supports examining emotions as explanatory pathways rather than treating them only as correlates of academic outcomes. The literature further indicates that positive achievement emotions tend to relate positively to academic outcomes, whereas negative emotions tend to relate negatively [24,33–35].

Even so, these pathways have been less consistently supported when they are tested through intervening processes. Emotional engagement is a theoretically coherent candidate because it links control and value appraisals with how students actually participate in school. However, studies remain limited and often rely on broad affective indices, making it unclear whether expectancy–value constructs and self-efficacy show comparable or distinct relations with emotional engagement and achievement when tested under parallel conditions.

### 1.4. Research gaps

There are two major gaps in the literature on motivational–emotional pathways to achievement that are especially relevant for secondary-school Physics.

First, emotional engagement is often operationalized through broad affective composites that obscure differences among class-related achievement emotions. This is especially problematic in Physics, where participation and performance are shaped by the interplay between perceived competence, task value, and the emotional demands of cumulative and evaluative content. Work has shown that emotions influence learning in Physics instruction, relate to retention in the Physics track, and matter for how students make sense of science learning experiences [36–38]. However, few researchers have tested structural models in which motivational beliefs are linked to performance partly through a hierarchically defined emotional engagement factor aligned with CVT.

Second, few researchers have directly compared alternative motivational perspectives on competence-related beliefs within the same structural framework to examine whether they yield convergent or differential patterns of association with achievement in Physics. This is relevant because competence-related beliefs in Physics are tied not only to current grades but also to students' broader positioning within the subject. Whitcomb et al. [39] showed that self-efficacy develops alongside interest, identity, belonging, and perceived recognition, whereas Basileo et al. [40] found that self-efficacy showed the strongest association with achievement and mediated the link between motivation and grades across two school subjects. Work with secondary-school students continues to document close associations between students' motivational beliefs and their achievement emotions, with such emotions in turn relating to academic engagement [41,42]. Together, these studies suggest that competence beliefs may be especially proximal to achievement, but this issue needs to be tested in subject-specific models that incorporate students' emotional experience during classroom learning.

These gaps are particularly relevant in Latin American contexts, where evidence on motivational–emotional pathways to achievement is limited. Emerging regional work suggests that achievement emotions are meaningfully associated with academic outcomes and may also shift alongside instructional interventions, underscoring the practical value of examining emotions as theoretically relevant mechanisms rather than merely as correlates [43].

### 1.5. This study

To address these gaps, we use a sample of upper-secondary students from Maldonado, Uruguay, and examine Physics performance as the main outcome. Using structural equation modeling, we compare two models in which GEE functions as an intervening variable linking motivational beliefs and achievement (Figure 1). One model evaluates expectancy and task value as predictors of GEE and performance; the other evaluates self-efficacy as a predictor of GEE and performance. This design enables a direct comparison of two motivational frameworks under parallel conditions. In both models, key sociodemographic and schooling covariates are incorporated as predictors of the motivational constructs, reflecting the known contextual patterning of motivation and achievement in secondary education [8,10]. We hypothesize that, in the expectancy–value model (H1), expectancy and task value will be positively associated with GEE and Physics performance, and that GEE will be positively associated with Physics performance. We further hypothesize (H2) that part of the association of expectancy and task value with Physics performance will be statistically represented through GEE. In the self-efficacy model (H3), self-efficacy will be positively associated with GEE and Physics performance, and GEE will be positively associated with Physics performance. We further hypothesize (H4) that part of the association between self-efficacy and Physics performance will be statistically represented through GEE.

This study makes three major contributions. First, we operationalize Emotional Engagement as a third-order latent factor grounded in discrete AEQ emotions, offering a CVT-consistent alternative to broad affective composites. Second, we directly compare self-efficacy and expectancy–value frameworks under parallel SEM conditions. Third, we add evidence from a Uruguayan secondary-school context, helping address the geographic imbalance in this literature and offering a model with potential relevance for school-based identification and intervention in Latin America. Together, these contributions frame the study as a theory-informed test of how motivational beliefs are related to achievement through students' emotional involvement in classroom learning.

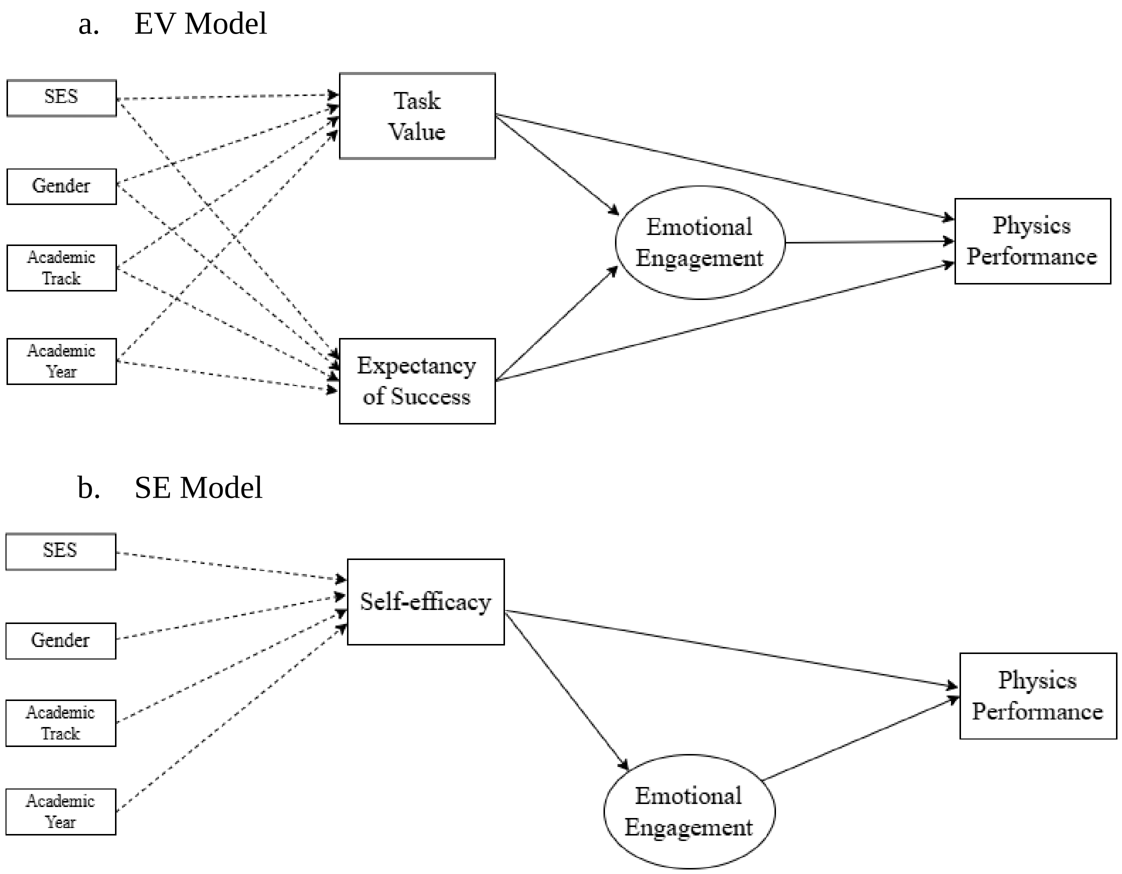



**Figure 1.** Hypothetical models tested.

## 2. Method

### 2.1. Participants

Using nonprobability convenience sampling, we recruited 340 upper-secondary students aged 15 to 18 years from Maldonado, Uruguay (M = 16.48, SD = 0.96), of whom 191 (57.4%) were boys and 142 (42.6%) were girls. Regarding age distribution, 60 (18.0%) were 15 years old, 106 (31.8%) were 16, 115 (34.5%) were 17, and 52 (15.6%) were 18. In terms of socioeconomic status, 105 (31.5%) were classified as low, 111 (33.3%) as medium, and 117 (35.1%) as high.

Because curricular track enrollment is a key feature of Uruguayan upper-secondary schooling, we harmonized students' programs into four comparable categories for analyses. In this sample, 56 (16.8%) were enrolled in a non-specialized track, whereas 45 (13.5%) were in Art and Design, 102 (30.6%) in Biosciences, and 130 (39.0%) in the Scientific-Technological track.

### 2.2. Instruments

#### *2.2.1. Sociodemographic questionnaire*

A questionnaire was administered to collect participants' sociodemographic information, such as gender, academic year, curricular track, and school shift, among other variables, and it included a short version of the Socioeconomic Status Index comprising the following indicators: family composition and educational level, health insurance provider, household income earners, housing condition and tenure, and household amenities [44]. Items were collected using direct, fixed-response questions; for example: "How many people usually live in this household (excluding domestic service)?", "How many household members receive income (from any source)?", "How many bathrooms does the dwelling have?", and "Does the household have air conditioning? If yes, indicate how many."

#### *2.2.2. Achievement emotions questionnaire*

The Uruguayan shortened version of the Achievement Emotions Questionnaire [45] used in this study consisted of 32 items rated on a five-point Likert scale, assessing eight class-related achievement emotions: enjoyment, pride, hope, shame, anger, anxiety, hopelessness, and boredom (four items per emotion); sample items included "I enjoy being in class" and "I feel nervous in class". For the emotional engagement measure, reliability was excellent based on polychoric correlations ($\omega$ = .98), with a substantial share of reliable variance attributable to the general factor ($\omega H$ = .76), consistent with the third-order hierarchical specification used to derive this variable.

#### *2.2.3. Expectancy of success scale*

An initial pool of ten items intended to measure expectancy of success was compiled from prior research using study-specific expectancy measures [8,12,46], mostly without reporting psychometric validation evidence. Item selection was refined through a pilot study. Two items shared by Carol Brown and David Putwain via personal communication were dropped because their removal improved psychometric functioning, and one reverse-coded item from Hulleman et al. [46] was removed because it generated confusion. The final version comprised four items: Two originating from Wigfield and Eccles [12], who used the label expectancy, for example "How well do you expect to do in Physics this year?", and two of the three items used by Hulleman et al. [46] to assess performance expectations, for example "I think I'll do well on the following sets of problems". Responses were given on a seven-point Likert scale, and the scale showed good internal consistency in this sample ($\alpha$ = .83, $\omega$ = .83).

#### *2.2.4. Motivated strategies for learning questionnaire*

To assess task value and self-efficacy, we used 13 items from two subscales from the adaptation by Curione et al. [47] of the abbreviated version of the Motivated Strategies for Learning Questionnaire [27], given that this instrument has been validated in Uruguayan university students. The task value subscale comprised seven items tapping primarily the extent to which students perceived Physics as interesting, useful, and important (e.g., "It is important for me to learn the material in this course"; "I think what I am learning in this course is useful for me to know"), but it did not include items assessing perceived cost, which is commonly considered part of the broader task value construct in expectancy–value theory. The self-efficacy subscale comprised six items (e.g., "My study skills are excellent compared with other students in this course"). In the present sample, internal consistency was adequate (task value: $\alpha$ = .92, $\omega$ = .92; self-efficacy: $\alpha$ = .86, $\omega$ = .86). Items were rated on a 7-point Likert-type scale (1–7). In Curione et al.'s [47] validation study, the reported coefficients were $\alpha$ = .83 for task value (labeled intrinsic value in that study) and $\alpha$ = .63 for self-efficacy.

#### 2.2.5. *Physics performance*

Physics performance was operationalized as the grade obtained in each student's last individual Physics assessment; grades from assessments completed in groups were not used because they complicate attribution of outcomes to individual students and may be distorted by group processes such as unequal participation and social loafing [48]. Grades were recorded on the Uruguayan 1–12 scale, where 6 is the minimum sufficiency grade. In this sample, performance was relatively high ($M$ = 8.68, $SD$ = 2.71) and showed negative skewness (skewness = −0.999), with approximately 90% of grades falling within the sufficiency range (6–12). This distribution aligns with patterns observed under grade inflation scenarios, which is a well-documented concern in many Western education systems, as it can distort incentives and introduce grading biases that prioritize immediate satisfaction over evidence of durable learning [49]. Twelve values were missing for this variable. Operationalizing achievement through a single teacher-assigned grade has known limitations for reliability, comparability across classrooms, and construct validity, because grades reflect not only demonstrated learning but also teacher-specific criteria, weighting, and grading standards. The negatively skewed distribution noted above was consistent with these concerns. We therefore treated the grade as an institutionally meaningful but imperfect indicator of Physics achievement and return to its limitations in the Limitations section.

### 2.3. Procedure

Meetings were held with the principals of each educational institution to present the research, the instruments, and to explain the ethical aspects. After school authorization, informed consent forms were distributed through classroom teachers to parents or legal guardians. Participation was voluntary, anonymity and responsible data use were assured, and the protocol had prior approval from a research ethics committee. Data were collected in classrooms using students' cellphones. Sociodemographics and psychological variables were assessed in August, and Physics grades were later obtained from teachers between October and November. This temporal separation meant that the motivational and emotional measures preceded the outcome by roughly two to three months. Although this ordering did not establish causality, it was consistent with the assumed direction of association, from earlier motivational and emotional appraisals to later graded performance, and reduced the likelihood that grades obtained at the end of the term shaped students' reports of their beliefs and emotions measured at the beginning.

### 2.4. Data analysis

Outlier detection combined three complementary procedures: univariate z-scores, with a cutoff of $|z| > 3.29$, as suggested by Tabachnick and Fidell [50], visual inspection of scatterplots to identify bivariate irregularities, and Mahalanobis distance for detecting multivariate outliers, using a significance level of $p < .001$ following recommendations from Pérez and Medrano [51]. Applying these criteria led to the removal of seven outlying cases; therefore, after excluding the twelve students with missing data on the outcome variable, as noted in the previous section, the final analytic sample consisted of 321 participants, which was a reasonable and sufficient sample size for the purposes of the study [52]. Missing data were confined to the Physics grade (12 cases, 3.7% of the cleaned sample). Because missingness affected only the outcome variable and was limited in extent, these cases were excluded listwise, the default treatment under the WLSMV estimator. Preliminary comparisons indicated that students with and without an available grade did not differ systematically on the focal motivational predictors, which was consistent with an at-random missingness pattern; nonetheless, the absence of an end-of-term grade for a small number of students was acknowledged as a limitation. Multicollinearity among the predictors was also examined: Variance inflation factors ranged from 1.00 (GEE) to 2.63 (expectancy of success), with all tolerances ≥ .38. These values were well below conventional cutoffs, and the models converged without estimation problems, indicating no evidence of problematic collinearity among the motivational and covariate predictors.

Both models were estimated in Mplus within a structural equation modeling framework. Because the Achievement Emotions Questionnaire indicators were specified as ordered categorical items, models were estimated using the weighted least squares mean- and variance-adjusted estimator (WLSMV). We used Theta parameterization, which is appropriate when categorical measurement models require direct modeling of residual variances [53,54]. Following standard practice, we estimated the hierarchical CFA for GEE within SEM to obtain model-based scores for the latent constructs and to preserve the measurement structure while estimating the hierarchical model [55] (see Supplementary Material 1). Structural relations were tested using a mixed approach; GEE was estimated from its ordinal item indicators, whereas Physics performance and the remaining variables in the structural models were included as observed variables, using previously computed scale scores when applicable. Given the hierarchical measurement model and the number of structural paths, the number of iterations was set to 20,000 to support stable convergence.

Model evaluation relied on standard global fit indices for categorical SEM, including the comparative fit index (*CFI*), Tucker–Lewis index (*TLI*), root mean square error of approximation (*RMSEA*), and the weighted root mean square residual (*WRMR*). Following commonly used conventions [56], *RMSEA* values < .08 were interpreted as indicating acceptable fit, whereas *CFI* and *TLI* were considered acceptable when > .90. Structural models were compared primarily on the basis of overall fit, parsimony, and the plausibility and magnitude of key structural coefficients. To diagnose localized misfit, we inspected modification indices and evaluated a minimally adjusted specification enabling theoretically plausible residual covariances.

Sociodemographic and schooling covariates (socioeconomic status, gender, academic track, and academic year) were incorporated as exogenous predictors of the focal motivational constructs, consistent with the conceptualization of these variables as distal contextual determinants of motivational beliefs and engagement.

Indirect effects were tested for the final model specifications as product-of-coefficients effects, with standardized estimates, standard errors, and 95% confidence intervals reported (delta-method confidence intervals, as bootstrap resampling was not available with the WLSMV estimator). A Monte Carlo simulation study estimated the expected statistical power to detect the hypothesized indirect effects using the same categorical SEM estimation framework and a sample size of 321. Results (see Supplementary Material 2) indicated acceptable parameter recovery, with moderate power for indirect effects in the expectancy–value model and higher power in the self-efficacy model. Because these estimates were based on the hypothesized baseline specifications, they did not incorporate the residual covariances introduced in the final adjusted models.

# 3. Results

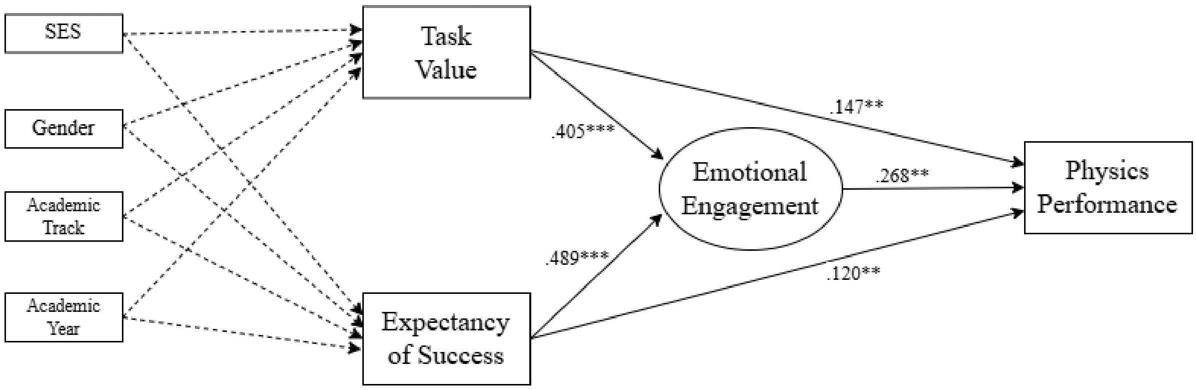
## 3.1. Expectancy–value model

The baseline model showed insufficient fit (*CFI* = .886, *TLI* = .879, *RMSEA* = .076, 90% *CI* [.072, .079], *WRMR* = 1.847). To address localized misfit, we tested a minimally adjusted specification by freeing two residual covariances in the third-order measurement model: enjoyment with boredom, and shame with anxiety. These associations were considered theoretically plausible because the paired emotions shared overlapping classroom-related content beyond the variance captured by the higher-order factors. Within Control–Value Theory, enjoyment and boredom were opposing activating–deactivating responses to the same ongoing classroom activity, so they tended to share method- and situation-specific variance (e.g., the same lessons and tasks evaluated as engaging vs. tedious). Likewise, shame and anxiety were negative, partly self-referential emotions evoked by evaluative and performance-related situations, and their items referred to closely related appraisals of threat and inadequacy. Enabling these two residual covariances therefore reflected local content overlap among specific emotion pairs rather than a substantive change to the hypothesized structure; no others were freed. These were also the only two residual covariances flagged by the modification indices, so freeing them was supported on both theoretical and empirical grounds. With these included, fit improved to acceptable levels (*CFI* = .920, *TLI* = .914, *RMSEA* = .064, 90% *CI* [.060, .068], *WRMR* = 1.591). The structural portion of the model accounted for 18.0% of the variance in Physics performance. Standardized estimates were coherent with the hypothesized structure, and the major structural relations were statistically significant (see Table 1 and Figure 2).

**Table 1.** Statistics from the EV model paths.

| **Path** | ***b*** | ***β*** | ***S.E.*** | ***z*** | ***p*** |
|---|---|---|---|---|---|
| Expectancy → Emotional Engagement | .461 | .489 | .044 | 5.54 | < .001 |
| Task Value → Emotional Engagement | .330 | .405 | .048 | 4.97 | < .001 |
| Expectancy → Performance | .224 | .120 | .041 | 2.82 | .005 |
| Task Value → Performance | .236 | .147 | .045 | 3.16 | .002 |
| Emotional Engagement → Performance | .530 | .268 | .081 | 3.11 | .002 |

Note. *b* = unstandardized coefficient; *β* = standardized coefficient; *S.E. = standard error (for the standardized estimate).*




Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Paths from covariates are displayed but not labeled to preserve figure readability. Academic track was entered through three dummy-coded contrasts; full standardized coefficients and *p* values for all covariate effects are reported in Table 2.

**Figure 2.** Path diagram of EV model with standardized coefficients.

With respect to the major pathways, expectancy and task value were positively associated with GEE, and GEE was positively related to Physics performance. Expectancy and task value also retained direct positive associations with performance, indicating that students with higher scores on these beliefs tended to obtain higher grades. The indirect associations of expectancy and task value with Physics performance through GEE were statistically significant (expectancy: $\beta = .131$, 95% *CI* [.053, .209]; task value: $\beta = .108$, 95% *CI* [.041, .175]). These results indicated that part of the association of each motivational belief with grades was statistically represented through GEE.

Regarding covariates, socioeconomic status, gender, and academic year were not significantly associated with either expectancy or task value (see Table 2). For academic track, Arts and Design was associated with lower expectancy and tended to be associated with lower task value, while Scientific-Technological was associated with higher task value; the remaining academic track contrasts were not statistically significant.

**Table 2.** Standardized associations of covariates with expectancy and task value.

| **Predictor** | **Expectancy *β*** | ***p*** | **Task Value *β*** | ***p*** |
|---|---|---|---|---|
| Socioeconomic status | .019 | .758 | .014 | .807 |
| Gender | .037 | .611 | .026 | .659 |
| Academic year | .110 | .194 | .089 | .223 |
| Track: Biosciences | −.091 | .465 | .037 | .714 |
| Track: Scientific-Technological | .107 | .382 | .257 | .007 |
| Track: Arts and Design | −.184 | .027 | −.117 | .089 |

Note. $\beta$ = standardized coefficient. Academic track coefficients represent contrasts relative to the reference category, ‘General track’.

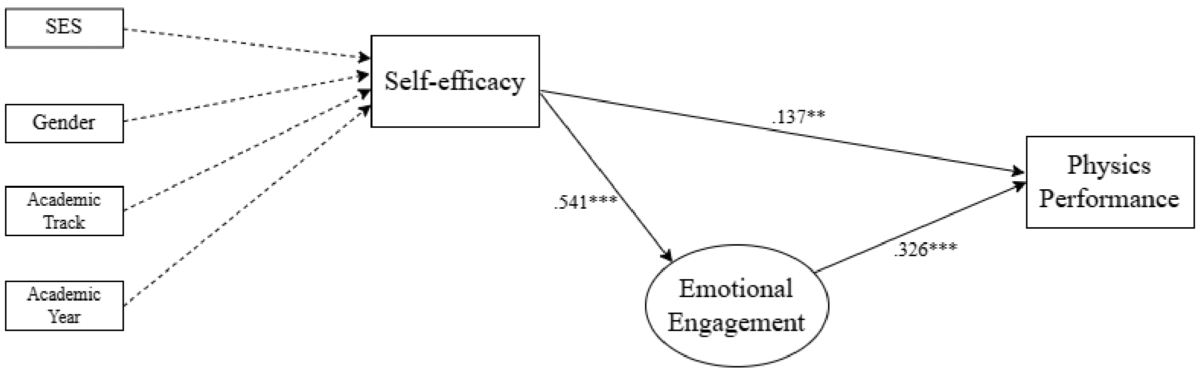
### 3.2. Self-efficacy model

Consistent with the previous model specification, we estimated this model enabling the same two theoretically plausible residual covariances (enjoyment with boredom; shame with anxiety). The model showed acceptable global fit (*CFI* = .942, *TLI* = .939; *RMSEA* = .056, 90% CI [.052, .059]; *WRMR* = 1.449), accounting for 17.3% of the variability in Physics performance. Standardized estimates indicated a well-specified model, and the key structural paths were statistically significant (see Table 3 and Figure 3).

**Table 3.** Statistics from the SE model paths.

| **Path** | ***b*** | ***β*** | ***S.E.*** | ***z*** | ***p*** |
|---|---|---|---|---|---|
| Self-Efficacy → Emotional Engagement | .443 | .541 | .066 | 4.45 | < .001 |
| Self-Efficacy → Performance | .249 | .137 | .046 | 2.90 | .004 |
| Emotional Engagement → Performance | .724 | .326 | .076 | 4.17 | < .001 |

Note. *b* = unstandardized coefficient; *β* = standardized coefficient;
*S.E. = standard error (for the standardized estimate)*




Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Paths from covariates are displayed but not labeled to preserve figure readability. Academic track was entered through three dummy-coded contrasts; full standardized coefficients and *p* values for all covariate effects are reported in Table 4.

**Figure 3.** Path diagram of the SE model with standardized coefficients.

In this model, higher self-efficacy was associated with higher general emotional engagement. Additionally, GEE was positively associated with Physics performance. Self-efficacy also showed a direct positive association with Physics performance, indicating that students who felt more efficacious tended to obtain higher grades in Physics. The indirect association between self-efficacy and Physics performance through GEE was also statistically significant ($\beta = .176$, 95% *CI* [.082, .270]), indicating that part of this association was statistically represented through emotional engagement.

With respect to the covariates predicting self-efficacy in this model, socioeconomic status, academic year, and gender were not statistically significantly associated with self-efficacy (see Table 4). For academic track, Arts and Design tended to be associated with lower self-efficacy, whereas Scientific-Technological was marginally associated with higher self-efficacy; the remaining academic track contrasts were not statistically significant.

**Table 4.** Standardized associations of covariates with self-efficacy.

| **Predictor** | ***β*** | ***p*** |
|---|---|---|
| Socioeconomic status | .037 | .663 |
| Gender | .025 | .788 |
| Academic year | .107 | .337 |
| Track: Biosciences | .016 | .920 |
| Track: Scientific-Technological | .253 | .095 |
| Track: Arts and Design | −.203 | .061 |

Note. $\beta$ = standardized coefficient. Academic track coefficients represent contrasts relative to the reference category, 'General track'.

### 3.3. Model comparison

Both structural equation models provided an acceptable representation of the data (Table 5). Fit indices indicated that the SE specification captured the covariance structure somewhat more closely. Differences in explanatory power, however, were modest: The EV model accounted for a slightly larger proportion of variance in Physics performance, whereas the SE model achieved comparable explained variance under a more parsimonious parameterization (i.e., fewer freely estimated parameters). Taken together, the results suggested a modest trade-off between explained variance and overall model fit.

**Table 5.** Structural equation models for predicting Physics performance.

| **Model** | ***k*** | $\chi^2$ | ***df*** | $\chi^2/df$ | ***RMSEA*** | ***RMSEA 90% CI*** | ***WRMR*** | ***CFI*** | ***TLI*** | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| EV | 201 | 1954.5 | 829 | 2.36 | .064 | [.060, .068] | 1.591 | .920 | .914 | .180 |
| SE | 191 | 1612.6 | 795 | 2.03 | .056 | [.052, .059] | 1.449 | .942 | .939 | .173 |

Note. $k$ = number of freely estimated parameters; $df$ = degrees of freedom; $R^2$ indicates the proportion of variance explained in the dependent variable (Physics performance).

The indirect pathways through GEE were statistically significant in both models and comparable in magnitude, with the self-efficacy pathway somewhat larger than the expectancy and task-value pathways (Table 6). This convergence indicates that GEE operated as a statistically relevant intervening variable under both motivational specifications, rather than being tied to a particular set of competence- or value-related beliefs.

**Table 6.** Standardized indirect effects through general emotional engagement.

| Model | Indirect path | *β* | *S.E.* | 95% *CI* | *p* |
|---|---|---|---|---|---|
| EV | Expectancy → GEE → Performance | .131 | .040 | [.053, .209] | .001 |
| EV | Task value → GEE → Performance | .108 | .034 | [.041, .175] | .001 |
| SE | Self-efficacy → GEE → Performance | .176 | .048 | [.082, .270] | < .001 |

Note. *β* = standardized indirect (product-of-coefficients) effect; *S.E.* = standard error; *CI* = delta-method confidence interval. GEE = General Emotional Engagement; *EV* = expectancy–value model; *SE* = self-efficacy model.

The hierarchical measurement model for GEE was essentially equivalent across the two specifications. In both models, standardized first-order loadings of the Achievement Emotions Questionnaire items on the eight emotion factors were substantial (range .61–.95), the second-order loadings of the emotion factors on the positive and negative valence dimensions were high (range .76–.92), and the third-order loadings defining GEE as a positive-versus-negative contrast were .80 (EV) and .76 (SE) in absolute value. Residual variances of the latent factors ranged from .16 to .58 in the EV model and from .16 to .71 in the SE model (Table 7). These values described the measurement model before the two residual covariances (between enjoyment and boredom and between shame and anxiety) were freed; as noted above, those were the only covariances indicated by the modification indices and were added in the final structural models reported here.

**Table 7.** Summary of the hierarchical measurement model for general emotional engagement in each structural model.

| Parameter | EV model | SE model |
|---|---|---|
| First-order loadings (range) | .62–.95 | .61–.95 |
| Second-order loadings (range) | .76–.92 | .76–.92 |
| Third-order loadings (\|λ\|) | .80 | .76 |
| Residual variances of latent factors (range) | .16–.58 | .16–.71 |

Note. Values are completely standardized estimates from the hierarchical measurement model estimated within each structural model, before enabling the enjoyment–boredom and shame–anxiety residual covariances. First-order loadings refer to items on the eight emotion factors; second-order loadings to emotion factors on the positive and negative valence dimensions; and third-order loadings to the two valence dimensions on GEE, specified as a bipolar contrast. All loadings were significant at $p < .001$. EV = expectancy–value model; SE = self-efficacy model.

## 4. Discussion

In this study, we compared two theoretically motivated SEMs, an expectancy–value (EV) specification and a self-efficacy (SE) specification, to predict Physics course grades, while examining emotional engagement as a potential intervening variable. Both models were supported by the data, but the SE specification showed the better combination of fit and parsimony, suggesting that competence-related beliefs may be especially proximal to graded performance in Physics. This interpretation is consistent with evidence suggesting that emotions can mediate the association between motivational beliefs and achievement [32]. More specifically, our findings align with science education research suggesting that emotions are not peripheral to science learning, but part of the processes through which students sustain attention, remain involved, and make sense of disciplinary activity. For example, Valdesolo et al. [57] argued that emotions such as awe can stimulate explanation and exploration in science learning, and Yonai and Blonder [58] showed that emotion induction in authentic science-learning environments can shape students' engagement with scientific activity. In light of this literature, our results suggest that emotional engagement in Physics classrooms is not merely an affective by-product of instruction, but one pathway through which motivational beliefs may be linked to academic performance.

Overall, the results supported the expected indirect-pathway pattern. In the EV model, expectancy and task value were positively associated with GEE and Physics performance, and GEE was positively associated with performance; direct paths from expectancy and task value to performance also remained significant. In the SE model, self-efficacy was positively associated with GEE and performance, and GEE was positively associated with performance. The paths from GEE to performance were stronger than the direct paths from the motivational beliefs to performance, suggesting that emotional engagement may be a more proximal pathway to achievement in the modeled system. Together with the statistically significant indirect effects reported above, this pattern is statistically consistent with partial mediation: Motivational beliefs were associated with grades directly and indirectly through students' emotional engagement. Because the design is non-experimental, however, these indirect effects are best understood as statistical pathways compatible with the proposed model rather than as evidence of a causal mediating mechanism.

From this perspective, the stronger fit and greater parsimony of the SE model suggest that competence-related beliefs may be more closely aligned with graded performance than broader expectancy–value appraisals in this context. This pattern is also broadly consistent with meta-analytic evidence in science education showing that self-efficacy displays stronger associations with science achievement than other attitudinal components, such as interest or perceived societal relevance [59]. In Physics classrooms, where success often depends on sustained work across cumulative content, capability judgments may be especially close to the processes that translate into grades. This interpretation is consistent with social-cognitive accounts in which self-efficacy shapes how students approach task demands, regulate effort, and persist under challenge. It is also compatible with evidence showing that self-efficacy can occupy a central place within motivational systems tied to achievement [39,40].

The EV results also indicate that expectancy and task value were not redundant, as both retained unique positive links with course grades alongside their associations with GEE. This does not mean that task value is theoretically secondary. Rather, it suggests that value may be expressed more clearly in outcomes that are not fully captured by a single-term grade, such as sustained study investment, persistence after setbacks, or intentions to continue in Physics.

Beyond the focal motivational predictors, the covariate results draw attention to the role of context, particularly academic track. Track differences are more plausibly interpreted as contextual markers of curricular exposure, peer composition, and institutional expectations than as indicators of intrinsic student differences. This reading is consistent with evidence that track placement can shape later educational trajectories even in systems oriented toward equal opportunity [3].

### 4.1. Expectancy–value, emotional engagement, and academic achievement

Within expectancy-value theory, task value is context-sensitive, so its effects may appear more clearly in effort, engagement, and choice than in grades alone [10]. This is compatible with science education findings showing that motivation and emotions are jointly implicated in students' engagement with science classes [31]. In this study, we extend that literature in two major ways. First, whereas much of the available science education research has examined emotions as parallel correlates of engagement, persistence, or science participation, our models tested emotional engagement as an intervening variable linking motivational beliefs with achievement in a subject-specific context. Second, by modeling emotional engagement as a higher-order construct based on discrete achievement emotions, the study offers a more differentiated alternative to broad positive-versus-negative affect indicators that are common in science education research. In that sense, the study contributes to science education not only by showing that emotions matter in Physics, but also by proposing a theoretically grounded way of modeling their role.

In our analyses, expectancy and task value were meaningfully related to students' emotional engagement in Physics, suggesting that their evaluations of the subject are reflected in how affectively involved they feel during classroom activity. Emotional engagement was positively associated with course grades, indicating that affectively engaged participation may help support the attention, persistence, and strategic effort that accumulate into performance across the term. In other words, students' evaluations of Physics may matter not only as cognitive judgments about usefulness or expected success, but also because they are reflected in the emotional quality of classroom participation, willingness to remain involved under challenge, and sustained engagement with disciplinary activity.

### 4.2. Self-efficacy, emotional engagement, and academic achievement

The model-comparison results also suggest that emotional engagement can be understood as a meaningful pathway through which competence beliefs are linked to achievement. Within social-cognitive and self-regulated learning accounts, self-efficacy is expected to shape effort, persistence, and responses to difficulty, thereby supporting more engaged participation and higher performance. Self-efficacy was directly related to performance and associated with emotionally engaged involvement during Physics learning.

This interpretation is also compatible with control–value theory: Stronger competence appraisals tend to co-occur with more adaptive emotional experiences, which can support self-regulation and achievement. In Physics, where students must often work through cumulative and conceptually demanding content, such appraisals may be especially relevant to whether challenge is experienced as manageable rather than discouraging.

### 4.3. Implications for classroom practice

If self-efficacy is relatively close to graded performance and partly operates through emotional engagement, classroom practice can target competence beliefs and students' day-to-day emotional experience in Physics. This implies designing classrooms that are intellectually demanding and emotionally sustainable. Instruction should communicate relevance and challenge while helping students build confidence in their ability to engage successfully with Physics tasks. Effective Physics instruction therefore needs to be not only cognitively demanding, but also emotionally sustainable. This point also helps clarify the study's relevance for science education beyond the local setting. International discussions in the field have increasingly emphasized that science learning depends not only on conceptual demand and instructional design, but also on whether students experience science as intelligible, worthwhile, and emotionally engaging. Our findings contribute to that discussion by suggesting that, in secondary-school Physics, emotionally sustainable classroom experiences may be one way in which motivational resources are translated into achievement. This interpretation is in line with intervention-based evidence from secondary chemistry showing that more participatory instructional formats can sustain higher positive emotions and lower negative emotions over time than conventional paper-and-pencil practice [60]. For Physics teaching specifically, this pattern suggests that instructional decisions should attend not only to the conceptual difficulty of the content but also to the emotional quality of classroom work. Because emotional engagement statistically carried part of the association between competence beliefs and grades, instructional approaches that help students experience demanding Physics tasks as manageable and worthwhile, rather than merely hard, may be especially consequential for sustained participation and, potentially, for persistence in the Physics track and related STEM pathways. This reading is consistent with school-based evidence that deliberately supporting students' engagement and emotional well-being can strengthen, rather than compete with, academic functioning [61].

To support self-efficacy, instruction can be designed to provide repeated mastery experiences: Tasks can be sequenced so students experience early success and then gradually face greater difficulty; formative checks and clear success criteria can reduce uncertainty; and worked examples or guided practice can help prevent early failure cycles that undermine confidence. Because grading can heighten pressure, learning-oriented assessment practices, such as low-stakes opportunities, revision options, and feedback-oriented rubrics, may also help protect efficacy and engagement.

Emotional engagement can be supported by making Physics content feel meaningful and by organizing participation so students are active contributors; for example, through peer instruction, prediction–observation–explanation routines, or brief collaborative sensemaking tasks. More concretely in Physics, this might involve inquiry-based and hands-on laboratory activities in which students design simple experiments, record measurements, and confront the gap between predictions and observed results; problem-solving scaffolds such as worked examples that fade into guided and then independent practice on kinematics or electricity problems; and routines that connect abstract formalisms to tangible phenomena (e.g., relating force diagrams to everyday motion). Such activities can sustain enjoyment and curiosity while reducing the anxiety and boredom often associated with cumulative, equation-heavy content. These strategies matter not because they motivate students in a generic sense, but because they can make Physics more intelligible, agentic, and emotionally sustainable. For classrooms and tracks in which Physics is experienced as more distant or less central, pairing mastery-structured tasks with relevance-building prompts and frequent formative feedback may be especially useful.

### 4.4. Limitations and future directions

Several limitations should be acknowledged. Motivational beliefs and achievement emotions were assessed in August, whereas Physics grades were obtained between October and November. Although this ordering is compatible with the proposed direction of association, the non-experimental design does not permit causal claims. Accordingly, the significant indirect effects should be interpreted as statistical pathways compatible with the proposed model, rather than as evidence that motivational beliefs causally affect grades through emotional engagement. The Monte Carlo results (Supplementary Material 2) further suggest that the indirect effects in the expectancy–value model, in particular, should be interpreted with caution, given the moderate statistical power estimated for these paths. In future studies, researchers should examine reciprocal relations over time and incorporate classroom-level variation in instructional practices.

In addition, because all psychological constructs were measured through self-report, some associations may partly reflect a shared method source. Researchers could strengthen validity through multimethod designs, including behavioral indicators, teacher ratings, or performance-based assessments. Moreover, because grades represent only one achievement indicator, researchers should examine whether expectancy–value variables show stronger incremental validity for outcomes more proximal to value, such as elective continuation, sustained study time, persistence intentions, and course choices.

Finally, because the sample was drawn from a specific geographical area of Uruguay and recruited through nonprobability convenience sampling, the generalizability of the findings is limited. Because schools and students were not randomly selected, the sample may over-represent institutions and classrooms that were more willing to participate, and it cannot be assumed to be representative of the country, or of Latin American secondary education more broadly. Self-selection of this kind can bias the estimated associations if willingness to participate is related to students' motivation, emotional engagement, or achievement, so the estimates should be read as specific to this sample rather than as population values. Replication across regions and intervention studies comparing efficacy-focused and value-focused supports would help clarify whether the pattern is specific to Physics or generalizes to other school subjects.

### 4.5. Conclusions

Overall, the findings support the relevance of emotional engagement in the association between motivational beliefs and Physics achievement in upper-secondary science education. Across both SEM specifications, motivational beliefs were positively associated with emotional engagement, which was positively associated with course grades, while direct paths from motivation to performance remained significant, and the indirect associations through emotional engagement were statistically significant in both models; a pattern statistically consistent with partial mediation, though not, given the non-experimental design, with a confirmed causal mechanism. Furthermore, model comparisons favored the self-efficacy specification as a more parsimonious and better-fitting account of Physics grades than the expectancy–value specification. Beyond these substantive results, the study contributes a hierarchically defined, Control–Value-consistent operationalization of general emotional engagement, derived from discrete achievement emotions rather than from a single global rating; this measurement approach may be useful for STEM education research seeking to model affect with greater theoretical precision. For practice, the findings point to the value of Physics classrooms that are simultaneously cognitively demanding and emotionally sustainable. Researchers should build on this design with longitudinal and intervention studies that can test the directionality of these associations and evaluate whether supporting competence beliefs and emotional engagement improves achievement and persistence in science. Taken together, these findings indicate that students' competence beliefs and their emotional engagement during classroom learning are closely connected and should be considered together in research on motivation and achievement in science education.

### Author contributions

Antonio Javier Casas: Conceptualization, methodology, data curation, formal analysis, investigation, funding acquisition, writing – original draft. Meimei Liu: Conceptualization, methodology, writing – review and editing. Gabriela Fernández-Theoduloz: Supervision, writing – review and editing. Victor Ortuño: Methodology, supervision. All authors read and approved the final manuscript.

### Use of Generative-AI tools declaration

The authors declare that Generative-AI tools were used exclusively for language support during the preparation of this manuscript, including wording refinement, readability improvement, and suggestions for alternative phrasing in selected passages. No AI tools were used to generate or analyze data, produce images or graphical elements, or make scientific or interpretive decisions. The authors fully reviewed and edited all AI-assisted outputs and take full responsibility for the final content of the manuscript.

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### Conflict of interest

The authors declare that there is no conflict of interest.

### Ethics declaration

All procedures performed in this study involving human participants were carried out in accordance with established ethical standards for research with human subjects. The study was approved by the Ethics Committee of the School of Psychology, University of the Republic (approval no. 191175-000013-23) and authorized by all participating schools. Informed consent was obtained from all participants and, in the case of minors, from their parents or legal guardians.

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