Anticipatory Emotions and Academic Performance: The Role of Boredom in a Preservice Teachers' Lab Experience

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Keywords

Experience Sampling Method; Anticipatory emotions; Active science teaching; Preservice teachers; Prior education; Achievement; Boredom

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Abstract

Affective experiences within academic contexts significantly influence educational outcomes. Despite this, the literature reveals a gap in generalising these effects to specific classroom activities, partly arising from the absence of suitable instruments to measure emotions in situational educational scenarios. Our study introduces an experience sampling method to measure sixteen discrete emotional states, deriving two scales for positive and negative activating emotions. Grounded in psychological and neuroscientific theories that integrate emotion with cognition, our research explores the interplay between prior knowledge, preservice teachers' anticipatory situational emotions, and subsequent learning in an experimental science education context. Analysing data from 269 preservice teachers from diverse backgrounds (STEM and non-STEM) at the upper-secondary level, we found that negative activating emotions are often rooted in non-STEM backgrounds and exacerbated by limited prior science knowledge. These negative emotions impact achievement and learning primarily through the mediating role of boredom. Furthermore, our results indicate that the detrimental impact of boredom on achievement is significantly influenced by prior knowledge, with a more pronounced effect on students with lower levels. Given that emotions are amenable to intervention, our findings propose that specifically addressing boredom in students with low prior knowledge could amplify the benefits of educational strategies.

Introduction

Education constitutes an emotive undertaking. Both students and educators experience emotions triggered by diverse antecedents such as subject matter, cognitive assimilation, pedagogical approaches, and retrospective and prospective achievements. These academic emotions can modulate teachers' and students' behaviour (Pekrun, 2014), influencing their decisions in teaching and learning processes (Mellado *et al.*, 2014), such as time management or learning strategy choice (Mega *et al.*, 2014). The emotional states within the classroom significantly influence educational outcomes (Camacho-Morles *et al.*, 2021; Goetz *et al.*, 2023). The Control-Value Theory of achievement emotions (a type of academic emotion related to achievement) posits that the perceived control over achievement activities and the perceived value of these activities and outcomes are the antecedents of achievement emotions, being these emotions the immediate antecedents of learning outcomes (Pekrun, 2014). Given emotions' impact on education, it is advised that teachers consider the affective elements of their pedagogy, particularly in science education, where disengagement often begins in late primary education through to secondary education levels, marked by an increase of negative emotions and a decrease in science valuation and self-efficacy (Mellado *et al.*, 2014). It is crucial to pinpoint, assess, and understand the sources of student emotions to tailor effective regulatory strategies and foster a conducive emotional climate for science engagement. Furthermore, preservice teachers need to understand their affective influence, as positive emotions towards science can inspire similar sentiments in students, given the transferability of teacher emotions (Frenzel *et al.*, 2009).

This study examines the association between preservice teachers' anticipated emotions before engaging in a laboratory activity and the resulting learning outcomes. Furthermore, we investigate how these emotions may be influenced by their prior educational experiences and knowledge. To initiate the study, we first introduce prevalent misconceptions related to emotions. Subsequently, we present a conceptual framework rooted in neurological and psychological perspectives to better understand emotions, their classification and their effect on learning.

Preventing Common Misconceptions

Emotions represent a complex aspect of human behaviour studied across various academic disciplines—psychology, neuroscience, philosophy, anthropology, and sociology—each offering unique interpretative frameworks, methodological approaches, and terminologies. The heterogeneity of these interdisciplinary analyses presents obstacles to the systematic study, research, and communication of emotional phenomena. Notably, the interchangeable use of emotion —physiological response— by feelings —subjective experiences— persists (Scherer, 2005) alongside a misapprehension of cognitive and emotional processes as separated mental faculties (Casado and Colomo, 2006). This dichotomy, which confronts cognition (traditionally associated with masculinity) in constant contention with emotion (associated with femininity), continues to influence the conceptualisation of human behaviour, thereby perpetuating gender stereotypes within the socio-cultural milieu despite its questionable empirical substantiation (Barret, 2017; Todd *et al.*, 2020). The enduring nature of these stereotypes accounts for the neglect of emotion studies in educational settings compared to cognitive studies.

Understanding Neurological and Psychological Conceptual Frameworks

From a neurobiological perspective, the Theory of Constructed Emotions (Barret, 2017) posits that "emotions are constructions of the world, not reactions to it". Accordingly, the brain continuously constructs concepts and creates categories to interpret internal and external sensory inputs such as physiological, cognitive, social, and cultural processes. It infers causal explanations for these inputs and predicts action plans in response (Barret, 2017). Emotions

serve as adaptive responses, predicting the most fitting rejoinder based on previous encounters with analogous stimuli, being considered an evolutionary predictive process humans use to subjectively evaluate their environment to estimate the future desirability of various stimuli and respond appropriately (Damasio and Carvalho, 2013; Barret, 2017). When the brain's internal model constructs a concept related to emotion, this categorisation process culminates in the experience of a specific emotional state. This state is not just a passive reaction but an active construction, integrating both external stimuli and internal cognitive processes. Students actively construct emotions across various tasks, subjects, settings and throughout their academic tenure.

From a psychological perspective, the Appraisal Theory of Emotion (Moors, 2020), in line with the Control-Value Theory (Pekrun, 2014), posits that emotional states or their constituents arise upon a subjective valuation of stimuli according to their congruence or incongruence with the individual's objectives and anticipations, the degree of their controllability, and the locus of their origination—whether it be external, internal, or attributable to impersonal factors. In the Theory of Constructed Emotions, these evaluative processes are seen as components of mental representations that anticipate potential actions to situational contingencies. These representations trigger emotional responses (physiological, cognitive, and motor) according to a perception-valuation-action (P-V-A) sequence that can be verbalised as feelings (Etkin *et al.*, 2015; Dixon *et al.*, 2017) (Figure 1). After an emotional response, the discrepancies between anticipated outcomes and actual situations are integrated into future predictive models that correct novel mental representations and emotional states. This concept is pivotal in understanding how emotions are formed and regulated over time (Etkin *et al.*, 2015; Barret, 2017; Moors, 2020). Teachers' and students' emotions may be related to past academic life events and future expectations. Since emotions can be regulated over time, they present ideal targets for educational interventions. Consequently, educators must understand the origins of emotions and how to manage them predictably.

Categorising and Classifying Emotions

Based on the P-V-A sequence, emotions are categorised according to the perceived focus (object or source of stimulus), the valuation conducted, and the resulting action (Pekrun *et al.*, 2023). While not exhaustive, if the focus is an educational activity or its achievements, these are academic emotions (such as enjoyment or pride). If they stem from knowledge acquisition, they are epistemic emotions (such as surprise, curiosity, or confusion). These may further pertain to distinct domains (e.g., Language, Mathematics, or Science), contexts (e.g., laboratory, outdoor, or classrooms), time frames (situational or course-specific), time relations (anticipatory or retrospective), duration of the emotion (state or trait), methodologies (e.g., active learning or teacher-centred), and so forth. Valuation considers sensory inputs, actions, physiological arousal, emotional state (Dixon *et al.*, 2017), competence, unexpectedness, and subjective value (Pekrun *et al.*, 2023). According to these appraisals, emotions are qualified as utilitarian (if their utility value is considered) or aesthetic emotions (derived from music or art, where utility is not a consideration). Emotions are also divided according to their valence: positive if the value prediction is that it will be beneficial for the individual, and negative if the prediction is adverse. Regarding action, emotions are classified as activating (high arousal) if they activate the physiological system (such as enjoyment) or deactivating (low arousal) if they inhibit action (such as boredom). The absence of a consistent and comprehensive categorisation of emotions in numerous studies compromises their comparability. Expressing a singular emotion, such as enjoyment, receives varied interpretations contingent upon the P-V-A sequence. For example, in academic settings, enjoyment may be induced by various stimuli, including acquiring knowledge, overcoming challenges, or a preference for specific subjects. While enjoyment is generally perceived as a manifestation of attraction towards stimulus (positive valence) and is associated with motivation in educational environments, it can also be counterproductive

(negative value), as a distraction, diminishing academic achievement (Tyng *et al.*, 2017). Nervousness towards mathematics as a whole is considered inhibiting, yet towards a specific problem, it could be activating (Tyng *et al.*, 2017). In other words, to achieve generalizability in emotion research and to facilitate the development of viable emotion regulation strategies, it is crucial to contextualise the focus of emotions, the appraisals involved, and the potential resultant actions. This contextualisation is more precise in immediate or situational events than past events or course-specific studies, commonly used to explore the interplay of emotions and learning (Pekrun *et al.*, 2023).

Emotions and the Learning Process

Both psychological and neurophysiological studies concur that emotions are intrinsically linked to students' learning processes and outcomes. Emotions govern attention, shape motivation to learn, and alter learning strategies, thus enabling a more focused engagement with pertinent information. Emotions influence human cognitive processes, encompassing perception, learning, memory, reasoning, episodic recall, cognitive control processes, decision-making, spontaneous thought, and problem-solving. (Tyng *et al.*, 2017; Likhtik *et al.*, 2019 Todd *et al.*, 2020). Furthermore, emotions facilitate long-term learning since emotionally charged information is more readily recalled than neutral information (Tyng *et al.*, 2017; Todd *et al.*, 2020). These insights support that emotion operates as a fundamental feature of cognition. Emotion regulates the flow of information across brain regions and, in conjunction with a suite of neuromodulators, ensures that emotional outcomes are the focal point of perception, thought, and action (Likhtik *et al.*, 2019; Todd *et al.*, 2020). Emotion dynamics such as valence shifts transform otherwise neutral experiences into meaningful, memorable events (McClay *et al.*, 2023). Given that the dynamics of emotional states shape the episodic structure of memory (McClay *et al.*, 2023), it is essential to examine the interplay between emotions and learning within the classroom context, in situ, where shifts in valence and arousal occur. However, most research on this interplay has focused on overall course performance rather than specific learning situations or methodologies (Pekrun *et al.*, 2009; Pekrun *et al.*, 2023). It is necessary to analyse the role of emotions in learning specific scientific content by assessing emotions and learning using temporally and situationally circumscribed measures. Such an approach would facilitate comparing and generalising research findings across various situational contexts. However, there is a substantial lack of studies conducted in real-life classroom settings (Goetz *et al.*, 2016; Vilhunen *et al.*, 2022; Pekrun *et al.*, 2023).

Assessing emotions

Although emotions are intrinsically personal (encompassing past experiences) and are variable processes that are situational, they manifest commonalities when individuals communicate their feelings, revealing variances across cultural contexts (Pekrun *et al.*, 2023). Emotions are often measured using self-report questionnaires (Mauss and Robinson, 2009). While these only capture a subset of the action programs elicited by human emotions (Damasio and Carvalho, 2013), they are associated with specific brain region activation, thereby bridging neurophysiological and psychological findings (Kragel *et al.*, 2016; Todd *et al.*, 2020). The Achievement Emotions Questionnaire (AEQ) stands out as a validated instrument for assessing eight emotions (6 to 12 items per scale) linked to academic activities and achievements, with its briefest version (4 items per scale) taking 15 minutes to administer (Bieleke *et al.*, 2021). While effective for tracking trait emotions over entire courses, it is less operative at capturing situational emotions within specific activities of less than one hour, contributing to the scarcity of situational emotions research.

Assessing situational (state) emotions requires validated experience sampling methods and instruments that can be rapidly administered without detriment to the ongoing activity or the assessment of situational emotions (Goetz *et al.*, 2016). Recent developments have led to less

intrusive methods, including facial recognition (Ezquerra *et al.*, 2023) and abbreviated questionnaires that preserve more extended versions' reliability and significant correlations (Gogol *et al.*, 2014; Kennedy *et al.*, 2016). Accumulated evidence supports the equivalence in reliability and validity between single-item and multi-item measures at the school level, providing teachers with information to orient their teaching practice (Gogol *et al.*, 2014; Kennedy *et al.*, 2016). Although single-item Likert scale ratings are commonly employed in emotion measurement, existing instruments often lack measurement invariance across different cohorts (Randler *et al.*, 2011; Schneider *et al.*, 2016).

We have recently designed and used a short instrument for assessing ten emotions via single-item measures. This instrument captures the emotional differences of students toward science lectures and practical sessions (Ochoa de Alda *et al.*, 2019). Furthermore, it has been utilised to examine shifts in emotions before and after an educational intervention in microbiology designed for preservice teachers (Marcos-Merino *et al.*, 2019). This instrument enables the extraction of two latent factors to explore the shared variance among five activating positive and four activating negative emotions, the analysis of their correlations with learning outcomes and the construction of a robust network of emotions and their influence on academic performance (Marcos-Merino *et al.*, 2022). The brief completion time of less than five minutes markedly minimised classroom disruptions. The instrument showed internal and external validity when measuring anticipatory emotions. Our previous findings corroborated earlier research on the link between emotions and academic achievement and showed that students lacking sufficient prior knowledge and those pursuing non-scientific upper-secondary education programs tend to anticipate more negative emotions. These emotions, in turn, were linked to subsequent learning, albeit with varying impacts: while frustration (a dampening emotion) hindered learning, nervousness (a stimulating emotional state) appeared to facilitate it (Marcos-Merino *et al.*, 2019; Marcos-Merino *et al.*, 2022).

This study

This study aims to carry out a conceptual replication of our previous study (Marcos-Merino *et al.*, 2019), substituting the microbiology lab experience with DNA extraction using household materials. In addition, we have expanded the discrete emotions measured by the instrument from ten to sixteen and have further validated and established the measurement invariance of the two latent factors: positive and negative activating emotions. Our findings reaffirm the regulatory function of emotions on achievement outcomes, with boredom emerging as a particularly influential factor. The observed differences between the two interventions—microbiology lab experience and DNA extraction—suggest that emotion regulations in classroom activities should be addressed on a case-by-case basis.

Methodology

Sample

This study involved a non-probabilistic sample of 269 preservice teachers (average age of 21 years, 62% female) pursuing a primary education degree at the University of Extremadura on two campuses (Cáceres and Badajoz) of the same Spanish region. All participants were enrolled in the Earth and Life Science Education course during Semester 6, across two consecutive academic years, a course that introduced them to the fundamentals of biology education. Concerning their prior education, 72% had a non-scientific Upper-Secondary Education degree (coded as non-STEM) in humanities, social sciences, or arts, while the remaining 28% held a scientific one (coded as STEM) (Table 1). The participant count exceeds the minimum required number of 262, as estimated using G*Power, based on an alpha level of 0.05 and an effect size of 0.2.

Procedure

Participants engaged in an experimental activity related to DNA extraction, implemented through guided inquiry. Briefly, this activity shows fundamental cell biology, physics, and chemistry concepts while highlighting science-technology-society interactions through various biotechnology applications. The teacher facilitated students' understanding of DNA extraction principles using everyday materials, guiding them through various problems, questions, and debates. Participants then developed and applied their extraction protocols to plant (tomato) and animal (saliva) samples. This activity has been validated and shown to be effective for active interdisciplinary science learning (Esteban *et al.*, 2019).

Before the activity, participants were informed of their participation's voluntary and anonymous nature, and that the results would not affect their course scores. All participants completed a pretest questionnaire assessing anticipatory emotions. After this, 192 participants completed a second questionnaire on scientific knowledge. In contrast, a separate subset of 77 participants did not complete the second questionnaire, serving as a control group to examine the effect of pretest completion on learning outcomes. The emotions questionnaire was administered first to prevent knowledge questionnaire resolution from interfering with anticipatory emotions. Fifteen days post-intervention, students submitted a report on the practice as part of the intervention, and 255 participants completed a posttest assessing subsequent knowledge. The study was approved by the University of Extremadura's Ethics Committee (registry 185/2021).

Instruments

Anticipatory emotions were assessed through an extended version of a previously validated quantitative self-report questionnaire (Ochoa de Alda *et al.*, 2019). This questionnaire was selected for its quick administration and reliability. Its structure is similar to the frequently used PANAS instrument, which contains two 10-item mood scales, allowing the extraction of two scales (Watson *et al.*, 1988). Our instrument scrutinised sixteen academic emotions and associated states that could potentially influence the course of the educational activity (Table 2). These emotions combine different dimensions of Pekrun's taxonomy: object focus (activity and outcome), valence (positive and negative), and arousal (activating and deactivating). The positive activating emotions (joy, enjoyment, enthusiasm, gratitude, pride, and awe) and the negative activating emotions (worry, frustration, nervousness, shame, fear, and disgust) were used to extract two latent factors, one for each valence: PAE (Positive activating emotions) and NAE (Negative activating emotions). Participants were prompted with the following inquiry: "What emotions do you anticipate experiencing when confronted with a DNA extraction practice using everyday materials?" This question effectively captured the subjective aspect of emotional experience, the temporal dimension (future emotions), and the specific object focus (the activity of DNA extraction with everyday material). All items were answered using a Likert-scale ranging from (1) not at all to (5) very much. At the onset of the questionnaire, participants provided information regarding their sex and prior educational background. Additionally, they generated an anonymous code to pair their pretest and posttest responses.

Scientific knowledge was assessed using a validated questionnaire with closed-ended test-type questions. The questions addressed common misconceptions among secondary school students and preservice teachers (Marcos-Merino and Esteban, 2018) and were based on key concepts from the Trends in International Mathematics and Science Study report (Foy *et al.*, 2013). Learning was assessed as a posttest score minus a pretest score.

Data Analysis

We analyse emotions both as discrete categories (i.e., joy and boredom) and as dimensions (PAE and NAE) since our brains use different representational dynamics that emphasise either

categories or dimensions (Giordano *et al.*, 2021). All descriptive and statistical analyses were conducted using Jamovi 2.48 (The Jamovi Project, 2023) and JASP 0.18.1 (Love *et al.*, 2019; JASP Team, 2023) software. We used G*power 3.1.9.6 (Faul *et al.*, 2009) for sample size calculation and statistical power analysis ($\alpha = 0.05$, Power = 0.80, Effect size = 0.3).

According to the Shapiro-Wilk test, the data did not follow a normal distribution (Table 3). Non-parametric statistical methods were employed, including Spearman correlation for variable interactions and Robust ANOVA to discern sources of variability in unbalanced subgroups lacking normality. For Robust ANOVA, we employed the Walrus module of Jamovi (Mair and Wilcox, 2020).

We used a confirmatory factor analysis (CFA), as implemented in the structural equation modelling module of JASP, to confirm the presence of two underlying latent factors (PAE and NAE) behind the subset of six positive and six negative activating emotions. We used an Oblimin rotation (Ochoa de Alda *et al.*, 2019). Since there is no agreement about the best model fit index for CFA of categorical data (Xia and Yang, 2019), we provide various fit indices and thresholds recommended to assess the adequacy of the model when using categorical data (Cheung and Rensvold, 2002; Xia and Yang, 2019; D'Urso *et al.*, 2022). These model fit indexes include χ^2 Test, Root Mean Square Error of Approximation (RMSEA), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI). χ^2 Test is sensitive to sample size, and it is shown for comparison. Cutoff criteria are shown together with the results. Predicted PAE and NAE factor scores were saved from CFA.

We use measurement invariance (MI) analysis to compare the equivalence of measures across groups (sex and prior education). We used CFA to define a sequence of nested models. Configural invariance was tested by fitting the two-factor model structure to different groups to see if the same general factor structure holds. Metric invariance was tested by constraining factor loadings to be equal across groups. Scalar invariance was tested by additionally constraining item intercepts to be equal across groups. The changes in χ^2 ($\Delta\chi^2$), RMSEA (ΔRMSEA), and CFI (ΔCFI) across the nested models were used to evaluate whether the construct was invariant at each of the stages of the multigroup analysis mentioned above. As recently recommended, a scale was considered non-invariant with respect to thresholds if both a significant χ^2 and at least one between a RMSEA > .01 or a CFI < −.01 was found (D'Urso *et al.*, 2022).

Statistical mediation and moderation analyses (MacKinnon *et al.*, 2007) were conducted using the Medmod module of Jamovi. For these analyses, the values of R^2 (proportion of explained variance), β (regression coefficient or relationship), and p (probability of observed results occurring by chance) were determined.

We used a network analysis (Network module of JASP) to estimate the graphical structure of a network of variables, within the framework of covariance selection models (EBICglasso estimator). This network represented variables as nodes and their interactions as edges. Two variables were connected if they correlated and shared the maximum unique covariance (Hevey, 2018).

Results and discussion

In the present investigation, we explore the impact of prior educational experiences on the anticipatory emotions of a cohort of preservice teachers as they approach a laboratory activity. This activity is designed to guide students through extracting DNA from tomatoes or saliva utilising commonplace household materials. Additionally, we analyse the predictive capacity of these emotions in fostering learning and academic achievement. To eliminate the possibility that variations in achievement stemmed from either teacher effectiveness or the learning gained during the completion of the pretest (Pyc and Rawson, 2010), we initially confirmed that the

posttest scores were independent of both the participants' campus (each with a different instructor, Mann-Whitney U test p-value 0.52) and the completion of the pretest (Mann-Whitney U test p-value 0.24). As is common in the demographic composition observed in educational degree programs, the cohort under study exhibits a demographic skew, with a preponderance of females and participants with a non-scientific orientation (non-STEM) during their upper secondary education tenure (Table 1).

Variability of discrete emotions

Participants were administered a questionnaire wherein they self-reported their feelings on a Likert scale. This encompassed six positive activating emotions (joy, enjoyment, enthusiasm, gratitude, pride and awe), six negative activating emotions (worry, frustration, nervousness, shame, fear and disgust), two positive deactivating emotions (confidence, and satisfaction), one negative deactivating emotions (boredom) and a cognitive state characterised as uncertainty. All the aforementioned items are conceptualised within the Control-Value Theory of Achievement (Table 2). Variability in participants' anticipatory emotions was observed, showing deviations from normal distribution for sex and prior education (Table 3). Considering this and the unbalance in sample size of subgroups (Table 1), we employed Robust ANOVA analysis to discern the sources of variability (Table 4). Concerning sex, our robust ANOVA analysis revealed that male participants exhibited greater expressions of gratitude ($p < 0.05$) compared to their female counterparts, alongside lower levels of uncertainty ($p < 0.01$). This contrasts with findings from a microbiology activity (Marcos-Merino *et al.*, 2022), where males exhibited greater confidence than females, pointing out that gender differences are likely specific to each science activity. These results align with previous research indicating gender differences in the expression of emotions, i.e., female preservice teachers often have more negative emotions and less positive emotions towards science than their male counterparts (Pekrun *et al.*, 2011; Chiang and Liu, 2014; Riegle-Crumb *et al.*, 2015).

Concerning the impact of prior education, participants with a scientific background during secondary education (coded as STEM) significantly anticipated fewer negative emotions, including shame, disgust, and worry, compared to their counterparts with a background in humanities, social sciences, or arts (coded as non-STEM) (Robust ANOVA, $p < 0.05$). This contrasts with findings from a microbiology activity (Marcos-Merino *et al.*, 2022), where a STEM prior education enhanced participants' positive emotions (confidence and satisfaction) but not negative emotions. These disparities in anticipatory emotions may be attributed to variations in prior experiences, as evidenced by the higher scientific knowledge level (pretest score) among participants with a STEM background (Table 5). Such knowledge is known to have a lasting impact on emotional responses (Pekrun *et al.,* 2017; Ochoa de Alda *et al.*, 2019). Our results confirm the impact of gender and prior education on anticipatory emotions and point out that this impact is different for each science activity.

Variability of PAE and NAE scales

Latent variables corresponding to Positive Activating Emotions (PAE) and Negative Activating Emotions (NAE) were examined via a two-factor model, as previously described (Mouratidis *et al.*, 2009; Chiang and Liu, 2014). Confirmatory Factor Analysis (CFA) results corroborate the acceptability of this model, with model fit indices demonstrating satisfactory fit: RMSEA = 0.068 (< 0.08 cut-off), TLI = 0.920 (> 0.90 cut-off), and CFI = 0.935 (> 0.90 cut-off) (Table 6). High McDonald's ω values (0.834 for PAE and 0.822 for NAE) support the internal consistency of the factors (Fornell and Larcker, 1981). The McDonald's ω composite reliability exceeding 0.6 validates the Average Variance Extracted (AVE) values for PAE and NAE (0.439 and 0.445, respectively) as acceptable (Fornell and Larcker, 1981), indicating a satisfactory variance capture relative to the variance attributed to measurement error. Moreover, the observed low Heterotrait-Monotrait (HTMT) ratio of correlations value of 0.142, substantially below the

threshold of 0.85 (Voorhees *et al.*, 2016), underscores robust discriminant validity, reinforcing the distinctiveness of the constructs (Table 6).

Configural invariance analysis showed that this two-factor model was also acceptable for the sex (males and females) and prior education (STEM, and non-STEM) subgroups since the three model fit indexes are under ($RMSE_{sex}$ 0.070<0.08; $RMSE_{prior\text{-}education}$ 0.075<0.08) and over (TLI_{sex} 0.917>0.90; $TLI_{prior\text{-}education}$ 0.935>0.90; CFI_{sex} 0.933>0.90; $CFI_{prior\text{-}education}$ 0.923>0.90) the cut-off criteria. This two-factor model was also acceptable for all subgroups when loadings and intercepts were constrained in metric invariance and scalar invariance analysis, respectively. Moreover, model differences were under the cut-off criteria, demonstrating metric and scalar invariances. Upon progressing from configural to metric invariance analysis by introducing loading constraints, the change in model fit did not reach statistical significance as per the χ^2 difference test [$\Delta\ \chi^2_{_sex}(10) = 18$, $p = 0.056$; $\Delta\ \chi^2_{_prior\ education}(10) = 17$, $p = 0.070$]. Concurrently, alternative fit measures supported acceptable changes: [$\Delta RMSEA_{_sex} = 0.001$ and $\Delta RMSEA_{_prior\ education} = -0.001$ (< 0.01 cutoff)] and [$\Delta CFI_{_sex} = -0.007$ and $\Delta CFI_{_prior\ education} = -0.007$ (< −0.01 cutoff)], thereby supporting the maintenance of metric invariance. Subsequent analysis, which incorporated intercept constraints, yielded an overall improvement in model fit without changes reaching statistical significance: [$\Delta\ \chi^2_{_sex}(22) = 0$, $p = 1$; $\Delta\ \chi^2_{_prior\ education}(12) = 0$, $p = 1$], [$\Delta RMSEA_{_sex} = -0.008$ and $\Delta RMSEA_{_prior\ education} = -0.008$ (< 0.01 cutoff)] and [$\Delta CFI_{_sex} = 0.011$ and $\Delta CFI_{_prior\ education} = -0.012$ (< −0.01 cutoff)], thus confirming scalar invariance. The measurement invariance analysis supported the feasibility of conducting meaningful comparisons across these subgroups. In contrast to that observed with discrete emotions, the variability of factor scores is not explained by sex or prior education (Table 7).

Associations between prior knowledge and emotions

Correlation analyses revealed negative associations between prior knowledge level (pretest score) and specific negative anticipatory emotions of participants, including nervousness (Spearman correlation = −0.156; p = 0.031), frustration (Spearman correlation = −0.158; p = 0.029), and shame (Spearman correlation = −0.184; p = 0.011). This confirms our previous findings on the association between prior knowledge of microbiology and nervousness and frustration (Marcos-Merino *et al.*, 2022).

In agreement, correlation analyses of latent factors based on emotion valence (PAE or NAE) showed that the pretest score was negatively related to NAE (Spearman correlation = −0.195; p = 0.007), but not significantly associated with PAE (Figure 2). These correlations were not significantly different according to sex or prior education (Figure 3). Overall, these results indicated that students who anticipated greater aversion to the activity possessed less prior scientific knowledge. Since these anticipatory emotions were situational (a laboratory activity), and the scientific knowledge derived from prior education, we reasoned that anticipatory emotions were modulated either directly by prior education (as supported by Robust ANOVA) or mediated by the knowledge acquired at this educational stage (as supported correlations). A mediation analysis showed that the effect of prior education on NAE (prior education →NAE; Total effect β=0,258; p=0.027) was partially mediated by prior knowledge (prior knowledge→prior education →NAE; β=0,106 p=0.026). These direct and indirect effects of prior education on emotions were similar to those observed before a microbiology activity, but in this case, the effect was on PAE, not NAE (Marcos-Merino *et al.*, 2022). These results indicated that preservice teachers with lesser scientific knowledge tend to anticipate more negative emotions (or less positive emotions) when facing the prospect of engaging in experimental science activities. Additionally, it unveils that an individual's prior education significantly affects not only their level of prior knowledge but also their anticipatory emotions. In agreement with preceding studies that explored the impact of past academic performance on emotions and the known effect of perceived competence and control on momentary emotions (Hayat *et al.*, 2020; Pekrun

et al., 2009; Pekrun *et al.*, 2017; Putwain *et al.*, 2018). Our results suggest that such perceptions of competence and control emerge not solely from students' understanding of the subject matter but also from their awareness of the constraints imposed by their lack of a background in STEM. Students' emotional experiences were influenced by their self-assessed knowledge and perceived limitations related to their educational background.

Earlier research has demonstrated that low learning outcomes in areas such as languages and mathematics often precede negative emotions (including boredom, anger, shame, and despair) across various educational stages (Pekrun *et al.*, 2009). The current study supports the predictive nature of past performance concerning negative anticipatory emotions in preservice teachers. While investigations into the interplay between learning and emotion during specific (situational) science activities among preservice teachers remain limited, the underlying cause of negative emotions and low self-efficacy in science among trainee teachers within the Spanish educational milieu is hypothesised to stem from their insufficient science training and subsequent withdrawal from science curricula post-secondary education (Bonil and Márquez, 2011; Brígido *et al.*, 2013; Mellado *et al.*, 2014). Previous research has also indicated that good academic results predict positive emotions such as enthusiasm, excitement, and pride; (Pekrun *et al.*, 2009; Pekrun *et al.*, 2017; Putwain *et al.*, 2018; Hayat *et al.*, 2020; Marcos-Merino *et al.*, 2022). However, this association was not observed in the present study.

Associations between anticipatory emotions, achievement, and learning

Prior knowledge correlates with achievement (Spearman correlation = 0.382; $p < 0.001$) and learning (Spearman correlation = −0.437; $p < 0.001$). According to linear regression analysis, prior knowledge explains 14.4% of the achievement variance [$\beta = 0.375 \pm 0.0674$ (Avg±SEM), $p < 0.001$; $R^2 = 0.144$], and explains 19.9% of learning variance [$\beta = 0.581 \pm 0.0946$ (Avg±SEM), $p < 0.001$; $R^2 = 0.199$]. The negative correlation between learning and prior knowledge indicates that participants with lower pretest scores benefit more from new learning, unlike those with higher scores who likely had this knowledge initially. In our previous study of anticipatory emotions before a microbiology activity, joy and enthusiasm were positively associated with achievement, while frustration and concern were negatively associated (Marcos-Merino *et al.*, 2022). In this study, the boredom of participants is the only discrete emotion associated with achievement (Spearman correlation = −0.145; $p = 0.020$) and learning (Spearman correlation = −0.165; $p = 0.041$). The ability of this anticipatory emotion to predict a decrease in achievement and learning was not unexpected since boredom reduces cognitive resources and task-related attention. The observed correlation coefficients for boredom's impact on achievement are marginally below the threshold previously reported (Tze *et al.*, 2016), which identified a stronger association within the range [−0.35, −0.25] in situational academic contexts. In agreement, the negative correlation between the achievement assessed at the end of the school year and the level of boredom measured at the same time point has been documented, as well as its predictive value for subsequent grades (Pekrun *et al.*, 2017). The mediation analysis revealed that boredom did not mediate the relationship between prior knowledge and learning outcomes or achievement. While previous studies have often reported this mediation effect, it appears to be non-uniform across different contexts. Recent evidence highlights this variability; for example, Tze and Li (2021) observed that boredom's mediation between cognitive appraisal and math achievement occurs in only about 47% of the educational systems examined. This underscores the complexity and situational nature of the mediating role of boredom in educational settings. Nevertheless, the analysis identified a significant mediating effect of boredom between negative anticipatory emotions (NAE) and educational outcomes: learning (NAE → boredom → learning; $\beta = -0.118 \pm 0.053$ (Avg ± SEM), $p = 0.025$; $R^2 = 0.255$) and achievement (NAE → boredom → achievement; $\beta = -0.076 \pm 0.036$ (Avg ± SEM), $p = 0.037$; $R^2 = 0.219$), indicating that boredom indeed plays a role in how negative anticipatory emotions affect both learning and achievement.

To deeply explore the relationship between achievement and boredom, we studied the relationship between prior knowledge and achievement at different boredom ratings (Figure 4).

The histogram displays a clear inverse relationship between median boredom levels and academic achievement, with higher boredom correlating with decreased median achievement scores on the corresponding Likert scale. This trend is supported by linear regression analyses that consider both achievement and prior knowledge, revealing that boredom's detrimental effect on achievement is accentuated among students with less prior knowledge. For instance, students with a high boredom rating of 4 and prior knowledge at 2.5 had an average achievement score of around 3. In contrast, those who did not anticipate boredom (rated 1 on the Likert scale) and identical prior knowledge tended to achieve significantly higher scores nearing 5. This pattern aligns with the correlation trend that higher achievement is associated with lower boredom.

Nevertheless, the achievement gap between different levels of boredom narrows with increasing prior knowledge, which diminishes the strength of the negative relationship between achievement and boredom. Notably, an inflexion point is observed in the data where boredom's impact on achievement reverses; beyond a certain level of prior knowledge (denoted by the intercept of regression lines in Figure 4), the relationship becomes positive—higher boredom corresponds with higher achievement. This counterintuitive effect, the reversal of boredom's impact, may explain the variability in the boredom-achievement correlation reported in the literature (Tze *et al.*, 2016), as it hinges on the level of prior knowledge. The prevalence of a negative correlation in our analysis can be attributed to the higher representation of participants with lower prior knowledge within our sample (separated by a red dashed line in the density maps of Figure 4). The differential effect of boredom fully agrees with boredom's mediating and moderating role in multiple-text comprehension. Boredom is negatively related to comprehension only for students with high word-reading fluency (Raccanello *et al.*, 2022), and we describe it for the first time in a science education context.

To methodically examine this relationship, we conducted a moderation analysis to discern how boredom anticipation influences the nexus between achievement and prior knowledge (Figure 5). Moderation analysis employs multiple regression to determine the impact of each variable (pretest scores and boredom levels) and their interaction (pretest*boredom) on posttest results (achievement). The analysis confirms that prior knowledge is a significant predictor of achievement [β=0.381±0.0698 (Avg±SEM), $p<0.001$], with the moderating effect of boredom substantially reducing this influence to β=0.209±0.0914 (Avg±SEM), (p=0.022). Further scrutiny of the moderation effect across various discrete emotions and states revealed that shame [β=0.1990±0.00817 (Avg±SEM), p=0.015], and uncertainty [β=0.1466±0.0561 (Avg±SEM), p=0.009], have a significant moderating impact on the relationship between pretest and posttest scores (Table 8). This comprehensive approach reinforces the importance of prior knowledge in academic achievement and highlights the multifaceted role that emotional states play in this dynamic.

These observations are consistent with previous studies highlighting the predictive value of anticipatory emotions on students' academic performance across various educational stages. In particular, the negative influence of boredom aligns with studies demonstrating that high prior intensity of this negative emotion predicts poor learning outcomes (Steinmayr *et al.*, 2016; Pekrun *et al.*, 2017). Previous research has also identified the predictive value of other positive and negative emotions (Marcos-Merino *et al.*, 2022), although these interactions were not observed in the present study.

Interplay of emotions and learning

Statistical network analysis (Hevey, 2018) integrated the relationships between anticipatory emotions and prior knowledge and learning, providing a systemic perspective of the relationships between these variables (Figure 6). The network's sparsity coefficient, at 0.627, indicates a high level of unconnectedness among potential variable pairings, except for three cluster structures. The first cluster encompasses NAE and boredom (sparsity=0.19), suggesting closer interaction within this grouping. The second cluster comprises PAE, satisfaction and confidence (all positive emotions) with dense interconnectivity (sparsity=0.143). The proximity of PAE and NAE discrete emotions in each cluster is consistent and adds validity to the two-factor model for PAE and NAE scales. The third, more diminutive cluster, consists of cognitive elements (prior knowledge and learning outcomes). The relatively low connectivity between PAE and NAE clusters agrees with the low correlation of these scales (Spearman correlation =0.154, p=0.011).

The observed network structure aligns with Pekrun's taxonomy of emotions (Pekrun *et al.*, 2017), where affective states are grouped according to their valence and activation properties. Notably, nervousness, though proximal to the negative emotions cluster, occupies a peripheral position, likely attributable to its classification as an emotional state, as opposed to a discrete emotion like fear, shame, or disgust. The distant positions of boredom and confidence from NAE and PAE, respectively, corroborate its characterisation as deactivating emotions. However, the central placement of satisfaction within PAE cluster presents an anomaly, given its classification as a positive deactivating emotion (Pekrun *et al.*, 2017). This suggests that the anticipation of satisfaction has an activating character.

The network also captures expected intra-cluster positive associations within positive and negative emotions and the anticipated negative interplay between boredom and joy. Intriguing is the positive correlation between enthusiasm and uncertainty, which may be attributable to the novelty and excitement of participants engaged for the first time in practical DNA extraction using household materials. The positive association between awe and uncertainty also supports this possibility. Additionally, the positive link between pride and shame, emotions with cognitive antecedents of success or failure, respectively, and traditionally seen as opposite (Pekrun *et al.*, 2023), suggests that participants may anticipate the feeling of shame they believe they can overcome.

The network mappings corroborate relationships identified in our previous study through alternative analytical approaches within this research, specifically the impacts of shame, frustration, and nervousness on prior learning and the influence of boredom on both achievement and learning. Furthermore, the networks reveal an unforeseen negative link between enjoyment and academic achievement. This association could reflect the potentially disruptive role of excessive enjoyment in learning contexts, possibly impeding achievement by diverting attention from task-related goals (Tyng *et al.*, 2017), which is consistent with the elevated excitement levels discussed earlier.

The results from the network analysis indicate that while negative emotions exhibit mutual interactions and modulation effects, it is predominantly boredom that mediates their impact on learning and achievement. Likewise, while positive emotions also show interconnectivity and modulation effects among themselves, enjoyment emerges as the principal emotion influencing learning. These insights present a notable divergence from the emotion-learning interplay before a microbiology laboratory session (Marcos-Merino *et al.*, 2022). In that study, despite the overall similarity of the network (the observed interplay and modulatory influence among both negative and positive emotions, and the similar effect of frustration and nervousness on prior knowledge), it was specifically frustration that negatively affected achievement, while nervousness had a positive impact. These findings underscore the relevance of contextual

investigation into emotional experiences to forecast emotional responses more accurately and potentially strategically influence them in an educational setting.

Concluding remarks

This study serves as a conceptual replication of prior research, examining whether the well-established impact of emotions on learning outcomes—traditionally documented in the context of courses and grades—is generalisable to preservice teachers engaged in laboratory activities. Results align with several previous research findings, including (i) the strong intercorrelation among negative emotions and within positive emotions; (ii) the latent factors behind negative and positive activating emotions; (iii) the minimal correlation between these factors;(iv) the measurement invariance across sex and prior education a; (v) the inverse relationship between negative emotions and both prior knowledge and achievement; and (vi) the mediating role of boredom in achievement and learning. This study supports the extension of prior research to preservice teachers' education and adds validity to our emotions assessment tool.

A key contribution of our research is integrating network analysis with traditional methods such as correlation, latent factor, mediation, and modulation analyses. Our network analysis elucidates the interrelationships between variables, mapping them based on their shared covariance. Within the network, boredom emerges as a pivotal element, influenced by NAE, inhibited by PAE, and negatively impacting learning and achievement. This central positioning of boredom aligns with findings from mediation and modulation analyses. Antecedents like prior education and learning appraisals, which negatively predict NAE, underscore the potential of interventions aimed at reshaping these appraisals—especially for non-STEM students—to enhance achievement. Furthermore, our results advocate for strategies that mitigate negative emotions, such as modifying experimental materials to decrease disgust, to foster better learning outcomes. Given that emotions are amenable to intervention, our findings propose that specifically addressing boredom in students with low prior knowledge could amplify the benefits of educational strategies.

In our prior research on emotions preceding a microbiology activity (Marcos-Merino *et al.* 2022), boredom was similarly situated centrally between NAE and PAE. Yet, in that context, it was frustration, rather than boredom, that detrimentally impacted learning. Moreover, in that study, nervousness (which used to negatively impact learning outcomes) had a counterintuitive positive effect on achievement. Here, we did not observe this association, but we observed another counterintuitive interaction, a negative association between enjoyment and learning. These non-univalent interactions of emotions and learning have been previously described (Tyng *et al.*, 2017) and underscore the importance of investigating the specific emotional dynamics and their regulatory mechanisms across various classroom activities to tailor emotional regulation strategies more effectively. It is essential to recognise that the impact of emotions on learning is not solely dependent on their valence. Some positive emotions, like enjoyment, can be detrimental to learning if experienced with high intensity or unrelated to specific scientific content. Likewise, a certain intensity of some stimulating negative emotions (e.g., nervousness) can enhance learning. During initial training, these factors should be considered.

Moreover, results support existing psychological and neuroscientific theories on the bidirectional emotion-cognition interaction and demonstrate its presence in a sample of future teachers in science education. The detected interactions highlight the importance of prior science learning experiences in shaping the anticipatory emotions experienced by preservice teachers, which influence their science learning during initial training. In the context of constructed emotion theory, emotional responses are predictive, drawing from past experiences in analogous situations to inform future behaviour. Anticipatory emotions thus act as a prism through which we can view a student’s previous experiences, whether favourable or

adverse, and gauge the corresponding level of arousal, which encompasses attention, motivation, and memory. This predictive quality of emotional responses is crucial for educational practitioners, as it facilitates tailoring classroom strategies from the outset. By reviewing and reinforcing requisite prior knowledge at the class's beginning, educators can ensure the accessibility of learning activities, regardless of students' educational backgrounds. The application of this straightforward pedagogical strategy could be instrumental in altering students' anticipatory emotional states, thereby reshaping their predictive landscape and potentially enhancing educational outcomes.

In conclusion, the present study reveals the complex interplay of anticipatory emotions, prior knowledge, and learning outcomes in preservice teachers. It underscores the importance of considering both positive and negative emotions in the teaching-learning process and the need for teachers to effectively manage and regulate their students' emotions. By recognising the potential effects of emotions on learning, teachers can adapt their teaching methods and classroom environments to foster an atmosphere that supports learning and emotional well-being.

Limitations and Future Research Directions

This study has several limitations. First, the participants were from the same context (same region, similar educational backgrounds, and the same training program), limiting the generalizability of the results. Second, the study relied on a quantitative self-report test of emotions, which measures feelings rather than actual emotions and might be subject to individual interpretation. Future research could use open-ended questionnaires or interviews for qualitative analysis to further explore the relationship between anticipatory emotions, prior knowledge, and other aspects of learning. The work is based on the assumption that participant expresses their emotions in relation to a focus (activity), but their expression can be related to other focuses.

Future research should further explore the relationships between different emotions and learning outcomes and investigate teachers' strategies to effectively manage and regulate their students' emotions. Additionally, longitudinal studies can help clarify anticipatory emotions' long-term effects on learning and academic achievement in various educational contexts.

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LEGENDS

Figure 1: Categorisation of the elements of emotional reactivity (Perception-Valuation-Action sequence) and emotion regulation.

Figure 2: Heatmap of intercorrelations. $^{*}p<.05$, $^{**}p<.01$, $^{***}p<.001$

Figure 3: Linear regression analysis showing the relationship between pretest scores and the factor scores of anticipatory negative (left panels) and positive (right panels) activating emotions, segregated by sex (top panels) and prior education (bottom panels). The density map of data distribution is represented on the axis, while the shaded area on either side of the straight line represents the standard error of the mean.

Figure 4: Scatter plot and linear regressions showing the impact of anticipated boredom levels on prior knowledge and achievement relationship. Boredom levels are rated on a Likert scale of 1 to 5 and depicted in varying colors of dots, lines, and boxes. Individual linear regression models represent the relationship between prior knowledge (pretest scores) and achievement (posttest scores) for each boredom level. The box plot shows the distribution of achievement across each boredom level, with the horizontal line within each box marking the median achievement (50th percentile) for that particular boredom level. Box-plot edges, 25th and 75th percentiles; whisker sizes, 1.5 × interquartile range (IQR); dots under and over the boxes are single data points. The density maps above the core diagram illustrate the dispersion of prior knowledge data across the spectrum (blue map at the bottom) and within specific levels of boredom (top map). A red dashed line extends from the intercepts of the regression analyses to the density maps, drawing attention to the concentration of data points associated with lower levels of prior knowledge.

Figure 5: Moderation analysis of boredom's influence on the relationship between Pretest (prior knowledge) and Posttest (achievement). The graph depicts the linear regression predicting Posttest scores based on Pretest scores at varying levels of the Boredom moderator (Average, Low (-1SD), and High (+1SD)). The moderation estimates table (top) presents the effect of

pretest scores on posttest, independent of boredom; the direct influence of boredom on posttest scores, without considering pretest scores; and the interaction effect (Pretest * Boredom), illustrating how the Pretest-Posttest relationship varies with different boredom levels. The simple slope estimates table (bottom) details the relationship between Pretest and Posttest scores for specific boredom levels.

Figure 6: Network plots of variables considering A) prior knowledge and learning and B) prior knowledge and achievement. Nodes (circles) represent variables identified by numbers in the left margin, except prior knowledge, achievement and learning, shown close to their yellow nodes. Edge weights (lines) represent the strength of association between variables. Blue edges represent positive associations, red edges represent negative associations; denser lines represent stronger connections. Arrows indicate the direction of interactions according to this study.

Figure 1

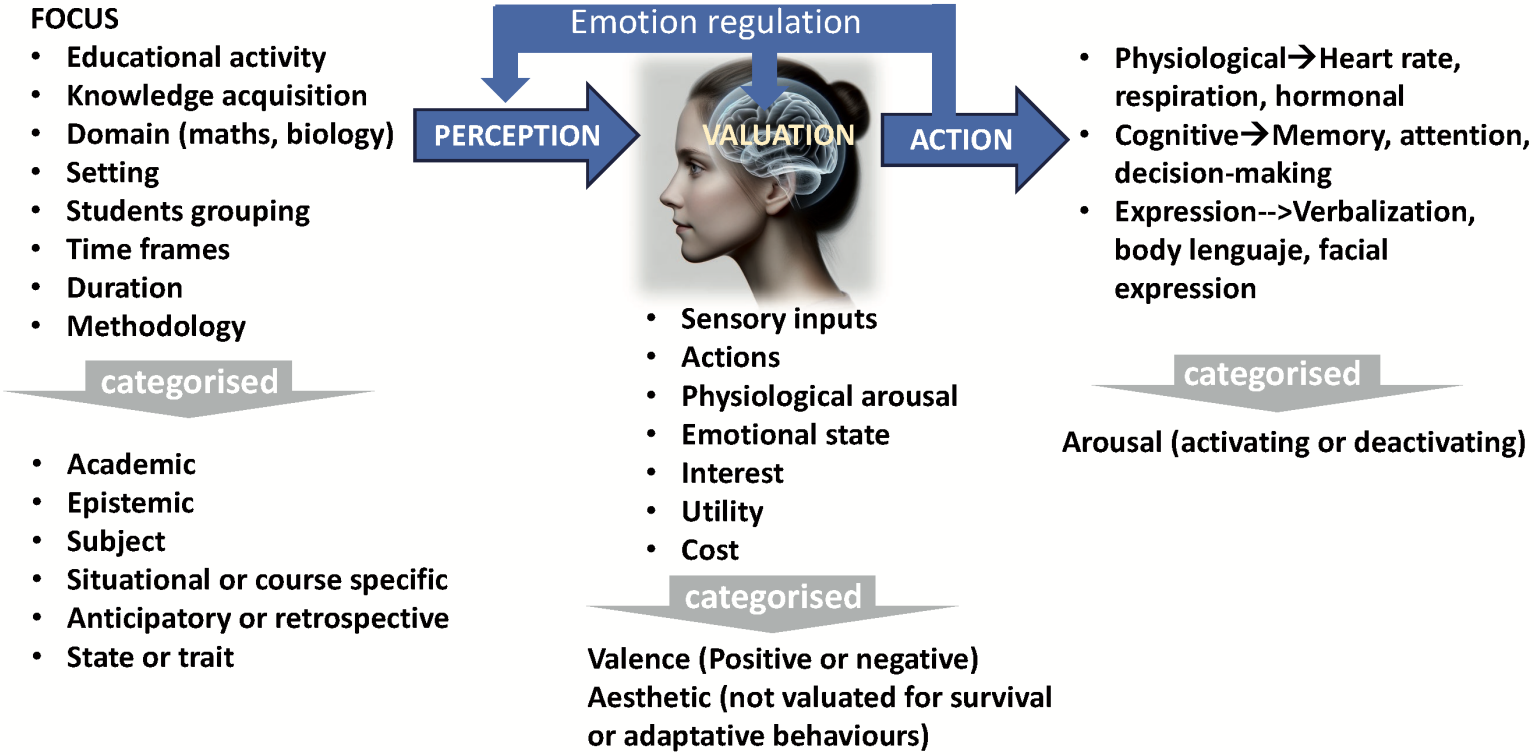

FOCUS
• Educational activity
• Knowledge acquisition
• Domain (maths, biology)
• Setting
• Students grouping
• Time frames
• Duration
• Methodology
categorised
• Academic
• Epistemic
• Subject
• Situational or course specific
• Anticipatory or retrospective
• State or trait
Emotion regulation
PERCEPTION
VALUATION
ACTION
• Sensory inputs
• Actions
• Physiological arousal
• Emotional state
• Interest
• Utility
• Cost
categorised
Valence (Positive or negative)
Aesthetic (not valuated for survival or adaptative behaviours)
• Physiological→Heart rate, respiration, hormonal
• Cognitive→Memory, attention, decision-making
• Expression-->Verbalization, body lenguaje, facial expression
categorised
Arousal (activating or deactivating)

Figure 2

		Pretest	Postest	Learning	PAE	NAE	Joy	Enjoyment	Enthusiasm	Gratitude	Pride	Awe	Worry	Frustration	Nervousness	Shame	Fear	Disgust	Confidence	Satisfaction	Boredom	Uncertainty
Knowledge	Pretest		0.382***	-0.437***	-0.037	-0.195**	-0.128	-0.068	0.07	-0.035	-0.035	-0.042	-0.109	-0.158*	-0.156*	-0.184*	-0.097	-0.137	-0.012	-0.028	-0.057	-0.083
	Postest	0.382***		0.644***	0.019	-0.057	0.019	-0.093	0.061	0.024	0.068	0.053	-0.09	-0.067	-0.031	-0.02	-0.025	-0.008	0.014	-0.007	-0.145*	0.005
	Learning	-0.437***	0.644***		-0.072	-0.027	0.04	-0.143	-0.056	-0.037	-0.046	0.004	-0.094	-0.072	0.044	-0.011	0.041	-0.019	-0.064	-0.015	-0.165*	0.028
Factors	PAE	-0.037	0.019	-0.072		0.154*	0.765***	0.763***	0.789***	0.659***	0.666***	0.699***	-0.015	0.079	0.234***	0.074	0.031	-0.017	0.416***	0.644***	-0.258***	0.184**
	NAE	-0.195**	-0.057	-0.027	0.154*		0.111	0.141*	0.02	0.037	0.113	0.209***	0.761***	0.721***	0.64***	0.622***	0.76***	0.596***	-0.118	0.109	0.363***	0.11
Discrete positive activating emotions	Joy	-0.128	0.019	0.04	0.765***	0.111		0.541***	0.53***	0.399***	0.36***	0.437***	-0.031	0	0.201***	0.057	0.002	-0.027	0.292***	0.49***	-0.311***	0.17**
	Enjoyment	-0.068	-0.093	-0.143	0.763***	0.141*	0.541***		0.515***	0.407***	0.405***	0.433***	-0.028	0.05	0.213***	0.033	0.074	0.02	0.282***	0.466***	-0.189**	0.127*
	Enthusiasm	0.07	0.061	-0.056	0.789***	0.02	0.53***	0.515***		0.425***	0.405***	0.468***	-0.071	-0.034	0.143*	-0.076	-0.066	-0.123*	0.428***	0.416***	-0.246***	0.241***
	Gratitude	-0.035	0.024	-0.037	0.659***	0.037	0.399***	0.407***	0.425***		0.504***	0.378***	-0.039	0.063	0.059	0.069	-0.07	-0.03	0.365***	0.529***	-0.092	0.082
	Pride	-0.035	0.068	-0.046	0.666***	0.113	0.36***	0.405***	0.405***	0.504***		0.442***	0.004	0.116	0.129*	0.178**	0.036	0.055	0.307***	0.495***	-0.069	-0.005
	Awe	-0.042	0.053	0.004	0.699***	0.209***	0.437***	0.433***	0.468***	0.378***	0.442***		0.086	0.196**	0.186**	0.129*	0.079	0.104	0.188**	0.515***	-0.152*	0.167**
Discrete negative activating emotions	Worry	-0.109	-0.09	-0.094	-0.015	0.761***	-0.031	-0.028	-0.071	-0.039	0.004	0.086		0.518***	0.432***	0.391***	0.518***	0.472***	-0.11	-0.041	0.299***	0.093
	Frustration	-0.158*	-0.067	-0.072	0.079	0.721***	0	0.05	-0.034	0.063	0.116	0.196**	0.518***		0.317***	0.45***	0.523***	0.468***	-0.08	0.148*	0.402***	-0.001
	Nervousness	-0.156*	-0.031	0.044	0.234***	0.64***	0.201***	0.213***	0.143*	0.059	0.129*	0.186**	0.432***	0.317***		0.333***	0.427***	0.199**	-0.028	0.098	0.092	0.286***
	Shame	-0.184*	-0.02	-0.011	0.074	0.622***	0.057	0.033	-0.076	0.069	0.178**	0.129*	0.391***	0.45***	0.333***		0.464***	0.471***	-0.093	0.112	0.301***	0.011
	Fear	-0.097	-0.025	0.041	0.031	0.76***	0.002	0.074	-0.066	-0.07	0.036	0.079	0.518***	0.523***	0.427***	0.464***		0.4***	-0.128*	0.053	0.345***	0.048
	Disgust	-0.137	-0.008	-0.019	-0.017	0.596***	-0.027	0.02	-0.123*	-0.03	0.055	0.104	0.472***	0.468***	0.199**	0.471***	0.4***		-0.101	0.052	0.249***	-0.019
Discrete deactivating emotions	Confidence	-0.012	0.014	-0.064	0.416***	-0.118	0.292***	0.282***	0.428***	0.365***	0.307***	0.188**	-0.11	-0.08	-0.028	-0.093	-0.128*	-0.101		0.303***	-0.126*	0.025
	Satisfaction	-0.028	-0.007	-0.015	0.644***	0.109	0.49***	0.466***	0.416***	0.529***	0.495***	0.515***	-0.041	0.148*	0.098	0.112	0.053	0.052	0.303***		-0.083	0.012
	Boredom	-0.057	-0.145*	-0.165*	-0.258***	0.363***	-0.311***	-0.189**	-0.246***	-0.092	-0.069	-0.152*	0.299***	0.402***	0.092	0.301***	0.345***	0.249***	-0.126*	-0.083		-0.101
Emotion related cognitive state	Uncertainty	-0.083	0.005	0.028	0.184**	0.11	0.17**	0.127*	0.241***	0.082	-0.005	0.167**	0.093	-0.001	0.286***	0.011	0.048	-0.019	0.025	0.012	-0.101	

Figure 3

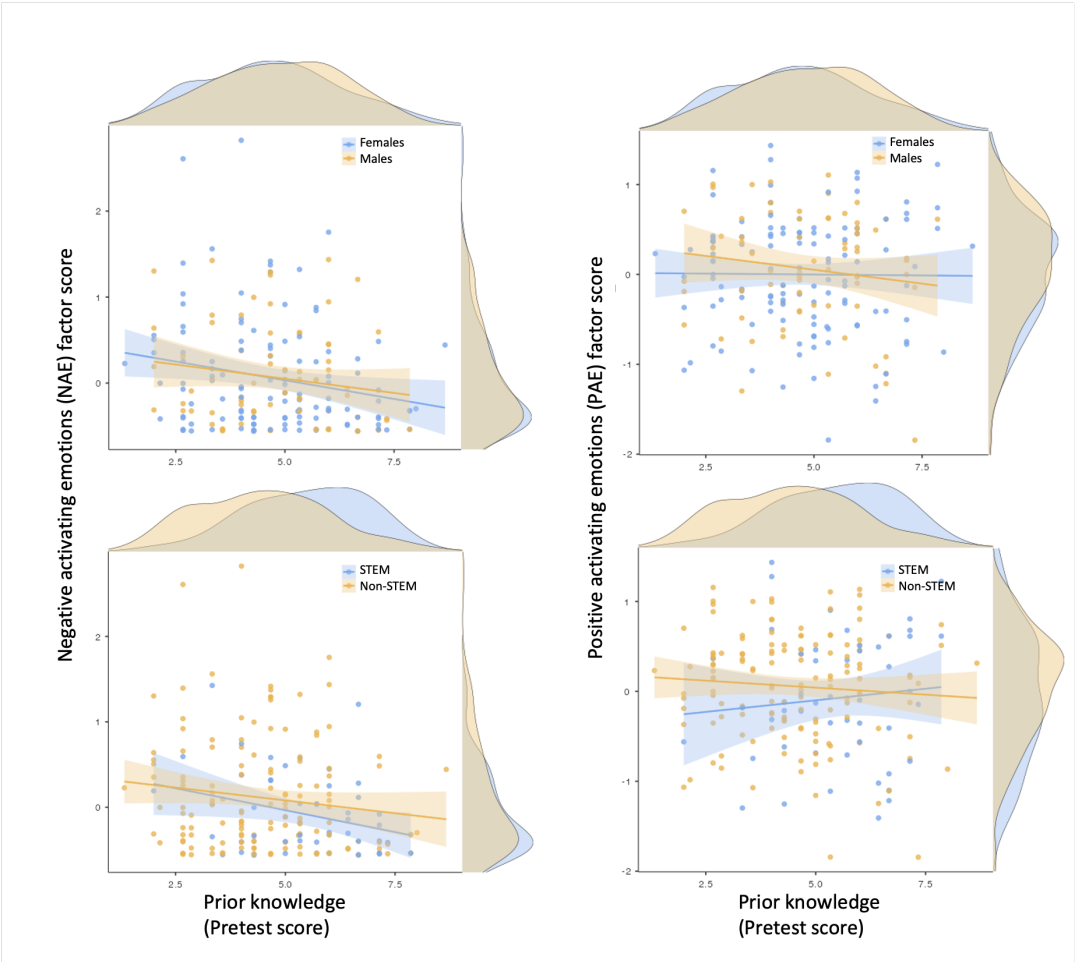

Negative activating emotions (NAE) factor score
Positive activating emotions (PAE) factor score
Females
Males
STEM
Non-STEM
Prior knowledge
(Pretest score)
2.5
5.0
7.5

Figure 4

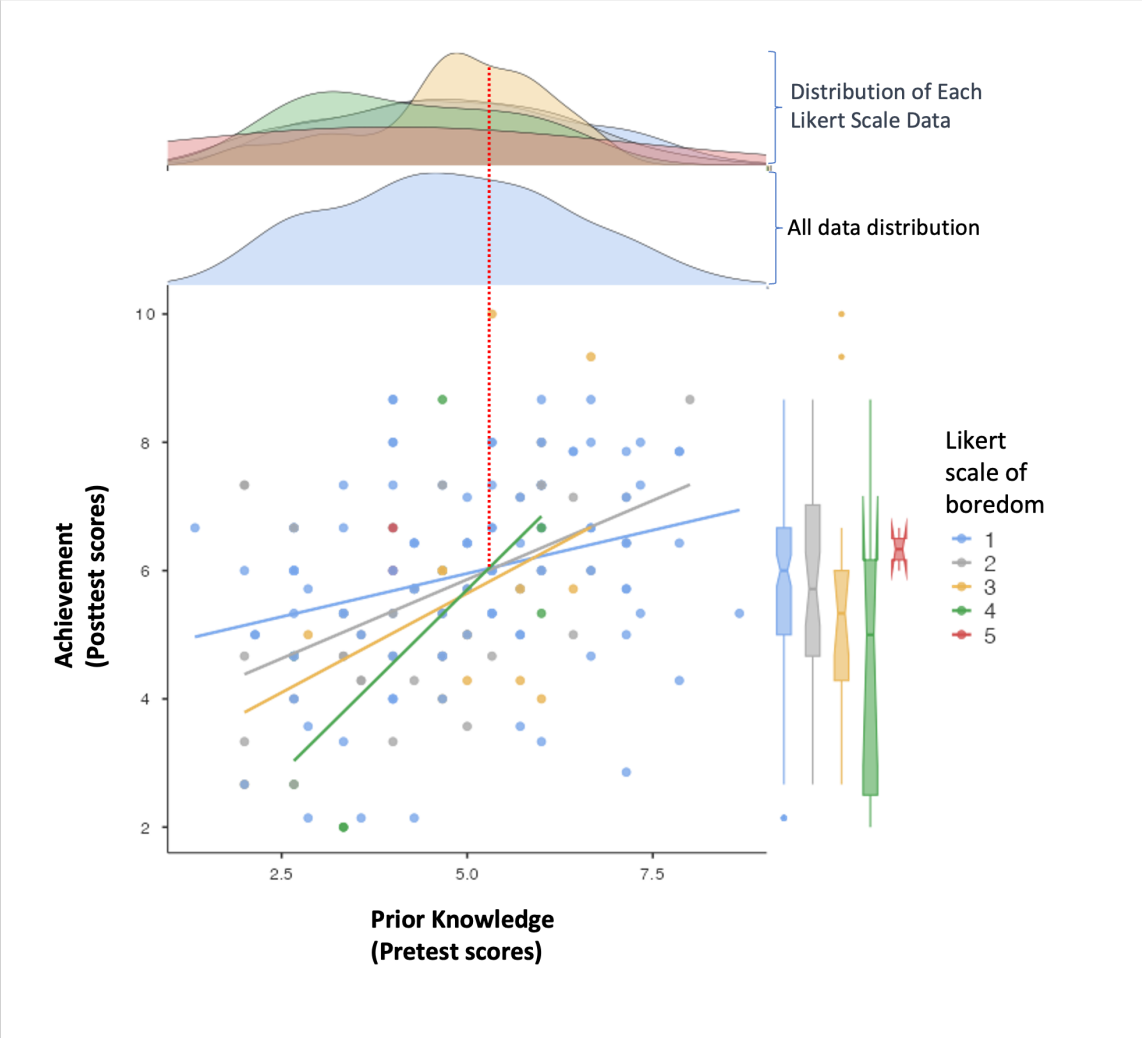
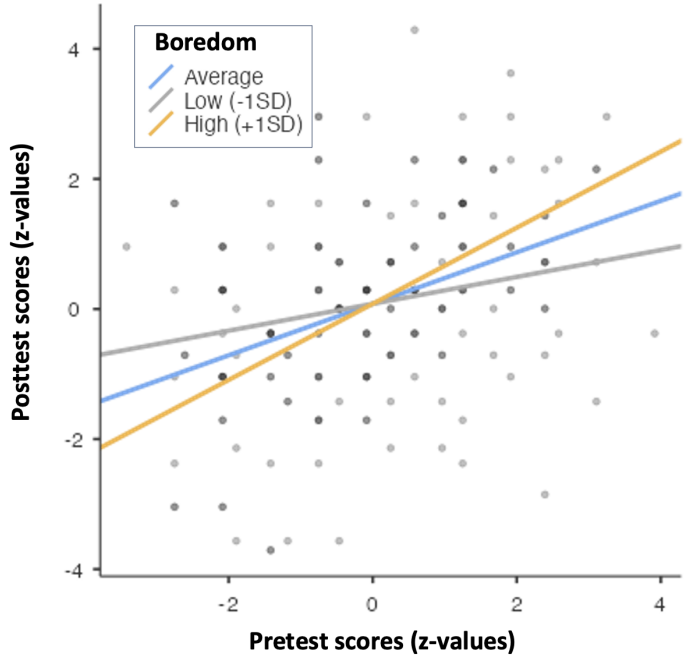

Distribution of Each
Likert Scale Data
All data distribution
Achievement
(Posttest scores)
10
8
6
4
2
2.5
5.0
7.5
Prior Knowledge
(Pretest scores)
Likert
scale of
boredom
1
2
3
4
5

Figure 5



Moderation Estimates

	Estimate	SE	Z	p
Pretest	0.381	0.0698	5.460	< .001
Boredom	-0.102	0.1309	-0.779	0.436
Pretest ✻ Boredom	0.209	0.0914	2.292	0.022

Simple Slope Estimates

	Estimate	SE	Z	p
Average	0.396	0.0709	5.59	< .001
Low (-1SD)	0.207	0.0998	2.07	0.038
High (+1SD)	0.585	0.1169	5.01	< .001

Figure 6

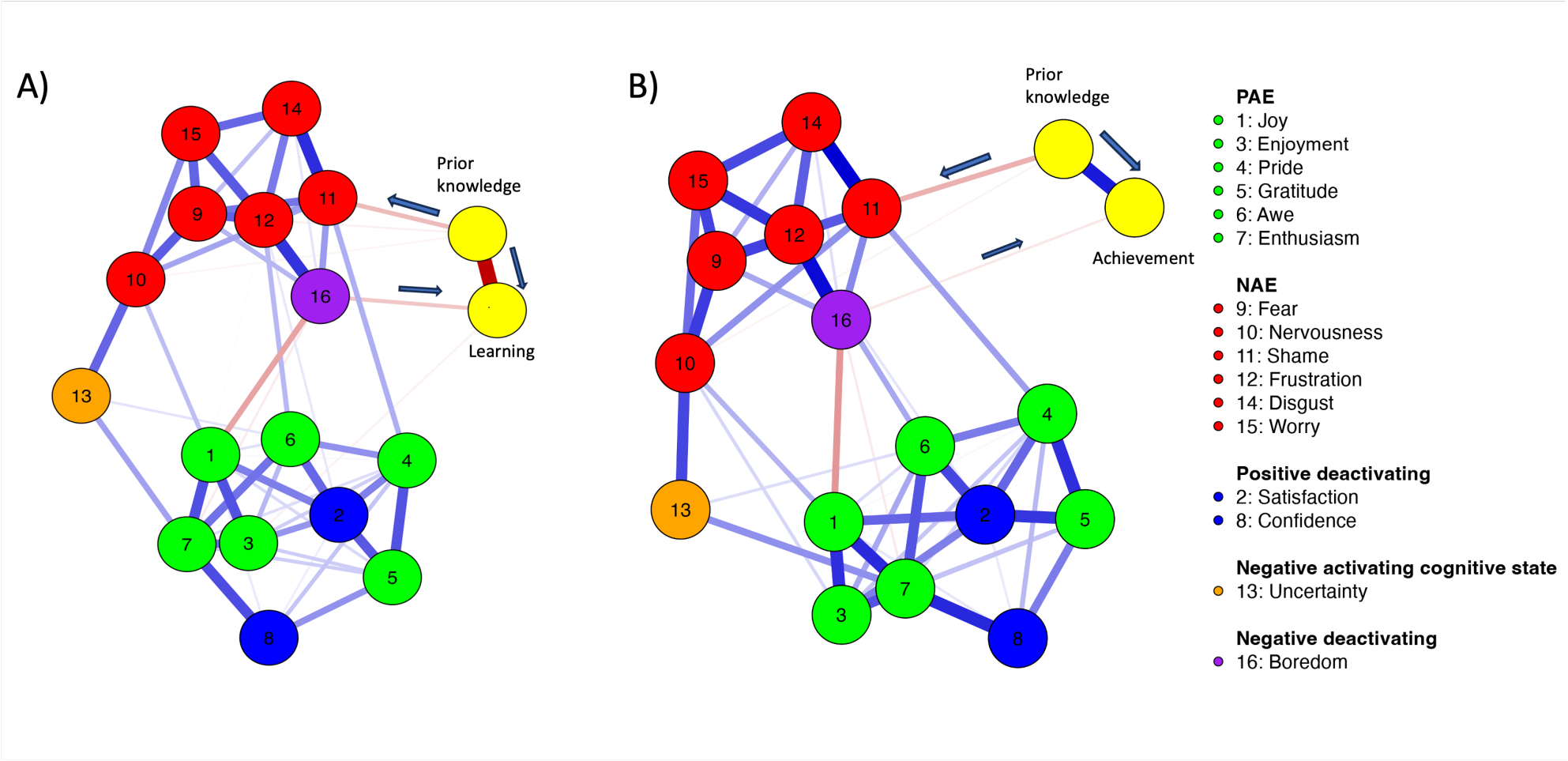

A)
Prior knowledge
Learning
B)
Prior knowledge
Achievement
PAE
1: Joy
3: Enjoyment
4: Pride
5: Gratitude
6: Awe
7: Enthusiasm
NAE
9: Fear
10: Nervousness
11: Shame
12: Frustration
14: Disgust
15: Worry
Positive deactivating
2: Satisfaction
8: Confidence
Negative activating cognitive state
13: Uncertainty
Negative deactivating
16: Boredom

Table 1: Participants distributed by sex and prior education during the upper secondary education itinerary (STEM or non-STEM).

Sex	Prior Education	N
Females	STEM	37
	Non-STEM	130
Males	STEM	37
	Non-STEM	65
TOTAL		**269**

Table 2: Characteristics and supposed triggering situation of feelings (as expression of the emotions, emotional responses, and cognitive states) involved in the study. Feelings are categorised according to Pekrun's three-dimensional taxonomy of achievement emotions in the frame of Control-Value Theory (Pekrun et al., 2023).

Feeling	Object focus	Valence	Activation	Relation to Control and value	Triggering situations (Students may feel this feeling when…)
*Joy	Outcome prospective (in this case)	Positive	Activating	Associated with high control and high-value perceptions.	they successfully perform the activity, demonstrating their ability to apply scientific concepts.
Enjoyment	Activity	Positive	Activating	Associated with valued activities.	they discover that the activity, e.g. scientific exploration, can be both educational and entertaining.
Enthusiasm	Activity	Positive	Activating	Associated with high value and interest.	they carry out practical activities, interacting directly with the material.
Gratitude	Outcome retrospective	Positive	Activating	Associated with valued activities.	they have the opportunity to engage in hands-on learning and receive support of their teachers and peers in understanding complex concepts.
Pride	Outcome retrospective	Positive	Activating	Linked high control perceptions.	they manage to successfully carry out an activity that requires their skills and knowledge.
Awe	Outcome prospective	Positive	Activating	Related to value perception of encountering profound knowledge or insights.	they feel inspired by the complexity and beauty of a subject, e.g. life at the molecular level.

Satisfaction	Outcome prospective	Positive	Deactivating	Linked to control and value perceptions.	they carry out a task with enthusiasm, effort, and understanding, and the result is successful and positive.
**Confidence	Outcome prospective	Positive	Deactivating	Relates to high control perceptions and self-efficacy.	they experience their subjective certainty to perform the experiment and understand the underlying principles.
Worry	Outcome prospective	Negative	Activating	Associated with low control perceptions.	they perceive unease about potential problems or difficulties during activity, e.g. making mistakes during the process, or concerns about outcomes.
Frustration	Activity	Negative	Activating	Associated with low control perception.	they perceive obstacles that hinder competent performance and the activity does not go as planned.
Nervousness	Activity	Negative	Activating	Associated with low control perceptions.	they respond to new, unfamiliar, or challenging situations (i.e., engaging in an activity they have never encountered before) thereby attaining this emotional state.
Shame	Outcome retrospective	Negative	Activating	Linked to low control.	they fail or do not yield the expected results.
Fear	Activity	Negative	Activating	Associated with low control and high value perceptions, such as fear of failure.	they perceive that they may make mistakes, damage materials, or not understand related concepts, e.g. when carrying out a practical DNA extraction activity.
***Disgust	Activity	Negative	Activating	Linked to low control and value.	they are uncomfortable handling the materials (e.g., saliva, fruits, or vegetables) used for DNA extraction.

Boredom	Activity	Negative	Deactivating	Linked to low value and low control perception.	the activity or environment does not cause stimulation or interest in them.
Uncertainty	Outcome prospective	Negative	Activating	Resulting from unclear control perceptions.	they encounter ambiguous situations or perceive a lack of knowledge required to perform an activity, thereby entering this cognitive state.

*Joy can be classified as outcome prospective or retrospective (Pekrun *et al*., 2023).

** The Spanish word Confianza (usually translated as Confidence) expresses a pleasant, relaxed emotional state involving subjective certainty about upcoming success, corresponding to the English word “assurance”. The English word confidence expresses mere certainty (Pekrun *et al*., 2023).

*** Disgust is scarcely addressed within the framework of Control-Value Theory, as, according to Pekrun (Pekrun *et al.,* 2002), "There was virtually no major human emotion not reported by our participants, with disgust being the only notable exception."

Table 3: Distribution of feelings reported by participants according to sex and prior education during the upper secondary education itinerary (STEM or non-STEM).

Emotion	Sex	Prior Education	Mean	SD	Shapiro-Wilk p-value
Joy					
	Females	STEM	3.70	0.909	<0.01
		Non-STEM	3.32	0.982	<0.01
	Males	STEM	3.19	0.995	<0.01
		Non-STEM	3.37	0.876	<0.01
Satisfaction					
	Females	STEM	3.08	1.19	0.005
		Non-STEM	2.95	1.06	<0.001
	Males	STEM	3.19	0.877	0.002
		Non-STEM	3.14	0.916	<0.001
Enjoyment					
	Females	STEM	3.49	1.12	0.003
		Non-STEM	3.31	0.979	<0.001
	Males	STEM	3.19	0.877	<0.001
		Non-STEM	3.43	0.951	<0.001
Pride					
	Females	STEM	2.84	1.36	0.003
		Non-STEM	2.55	1.10	<0.001
	Males	STEM	2.73	1.07	<0.001
		Non-STEM	2.97	0.968	<0.001
Gratitude					
	Females	STEM	3.00	1.27	0.006
		Non-STEM	3.07	0.990	<0.001
	Males	STEM	3.22	0.917	0.002
		Non-STEM	3.42	1.04	<0.001
Awe					
	Females	STEM	2.70	1.41	<0.001
		Non-STEM	3.02	1.13	<0.001
	Males	STEM	2.95	1.18	0.008
		Non-STEM	3.23	1.11	<0.001

Enthusiasm					
	Females	STEM	3.92	1.12	<0.001
		Non-STEM	3.42	1.04	<0.001
	Males	STEM	3.32	1.16	0.006
		Non-STEM	3.60	0.880	<0.001
Confidence					
	Females	STEM	3.59	1.01	0.002
		Non-STEM	3.22	0.998	<0.001
	Males	STEM	3.24	0.893	<0.001
		Non-STEM	3.52	0.920	<0.001
Fear					
	Females	STEM	1.51	0.768	<0.001
		Non-STEM	1.53	0.873	<0.001
	Males	STEM	1.38	0.594	<0.001
		Non-STEM	1.57	0.865	<0.001
Nervousness					
	Females	STEM	2.11	1.13	<0.001
		Non-STEM	2.26	1.14	<0.001
	Males	STEM	2.03	1.14	<0.001
		Non-STEM	2.22	1.08	<0.001
Shame					
	Females	STEM	1.14	0.419	<0.001
		Non-STEM	1.42	0.806	<0.001
	Males	STEM	1.32	0.709	<0.001
		Non-STEM	1.52	0.793	<0.001
Frustration					
	Females	STEM	1.43	0.765	<0.001
		Non-STEM	1.45	0.779	<0.001
	Males	STEM	1.41	0.644	<0.001
		Non-STEM	1.49	0.687	<0.001
Uncertainty					
	Females	STEM	3.43	1.34	<0.001
		Non-STEM	3.58	1.13	<0.001
	Males	STEM	2.92	1.12	0.004
		Non-STEM	3.20	1.15	<0.001

Disgust					
	Females	STEM	1.22	0.534	<0.001
		Non-STEM	1.56	0.988	<0.001
	Males	STEM	1.27	0.608	<0.001
		Non-STEM	1.40	0.787	<0.001
Worry					
	Females	STEM	1.43	0.728	<0.001
		Non-STEM	1.79	0.962	<0.001
	Males	STEM	1.65	0.889	<0.001
		Non-STEM	1.85	0.922	<0.001
Boredom					
	Females	STEM	1.41	0.762	<0.001
		Non-STEM	1.45	0.845	<0.001
	Males	STEM	1.54	0.767	<0.001
		Non-STEM	1.69	0.917	<0.001

Table 4. P-values from robust ANOVA assessing the significance of sex and prior education in explaining the variability of feelings, using a trimmed means level of 0.2. Interaction (Sex*Prior Education) p-values are not shown due to non-significance (p > 0.05).

	Joy	**Satisfaction**	**Enjoyment**	**Pride**	**Gratitude**	**Awe**	**Enthusiasm**	**Confidence**
Sex	0.189	0.126	0.447	0.236	**0.038**	0.185	0.088	0.872
Prior Education	0.972	0.925	0.476	0.885	0.435	0.097	0.19	0.375

	Fear	**Nervousness**	**Shame**	**Frustration**	**Uncertainty**	**Disgust**	**Worry**	**Boredom**
Sex	0.782	0.590	0.298	0.428	**0.007**	0.583	0.305	0.056
Secondary Education	0.940	0211	**0.041**	0.658	0.319	**0.008**	**0.033**	0.653

Table 5. P-values from robust ANOVA assessing the significance of sex and prior education in explaining the variability of prior knowledge (pretest scores), achievement (posttest scores), and learning (posttest minus pretest), using a trimmed means level of 0.2. Interaction (Sex*Prior Education) p-values are not shown due to non-significance (p > 0.05).

	Prior knowledge	Achievement	Learning
Sex	0.926	0.103	0.483
Secondary Education	0.001	0.001	0.757

Table 6. Model fit statistics for CFA of the two-factor model for positive activating and negative activating emotions scales (Top section), its MI across sex and prior education at each level of invariance testing, along with the changes in model fit (Middle section) and the cutoff criteria for model fit (Bottom section). Difference test reflects the fit change relative to the preceding model; (p), p-value of χ^2; ΔCFI, change in comparative fit index relative to the preceding model; ΔRMSEA, change in root mean square error of approximation relative to the preceding model.

Confirmatory factor analysis										
		Model fits					**Factor metrics**			
Model		**χ^2**	**df. (p)**	**RMSEA 90% CI**	**TLI**	**CFI**	**Factors**	**ω**	**AVE**	**HTMT**
Baseline model		118	53 (<0.001)	0.068 (0.051-0.084)	0.920	0.935	PAE	0.834	0.439	0.142
							NAE	0.822	0.445	
Measurement Invariance		**Model fits**					**Model fit difference test**			
Groups	**Model**	**χ^2**	**df. (p)**	**RMSEA 90% CI**	**TLI**	**CFI**	**Δ χ^2**	**Δ df.**	**Δ RMSEA**	**Δ CFI**
Sex	*Configural invariance*	176	106 (<0.001)	0.070 (0.051-0.088)	0.917	0.933	-	-	-	-
	Metric invariance	194	116 (<0.001)	0.071 (0.053-0.088)	0.915	0.926	18	10 (0.056)	0.001	-0.007
	Scalar invariance	194	128 (<0.001)	0.062 (0.043-0.079)	0.935	0.937	0	22 (1.000)	-0.008	0.011
Prior education	*Configural invariance*	185	106 (<0.001)	0.075 (0.056-0.092)	0.904	0.923	-	-		-
	Metric invariance	203	116 (<0.001)	0.074 (0.057-0.091)	0.904	0.916	17	10 (0.070)	-0.001	-0.007
	Scalar invariance	203	128 (<0.001)	0.066 (0.048-0.083)	0.925	0.928	0	12 (1.000)	-0.008	0.012
Cut-off criteria for										
Good fit				<0.06	>0.95	>0.95				
Acceptable fit or difference			>0.05	<0.08	>0.90	>0.90		p>0.05	Δ<0.01	**Δ**≤-0.01

df, degrees of freedom; RMSEA, root mean square error of approximation; 90% CI, 90% confidence interval around RMSEA; TLI, Tucker–Lewis index; CFI, comparative fit index; ω: MacDonald's ω for composite reliability of internal consistency; AVE: Average Variance Extracted; HTHT: Heterotrait-monotrait ratio of correlations.

Table 7. P-values from robust ANOVA assessing the significance of sex and prior education in explaining the variability of PAE and NAE factor scores, using a trimmed means level of 0.2. Interaction (Sex*Prior Education) p-values are not shown due to non-significance (p > 0.05).

	PAE	**NAE**
Sex	0.929	0.733
Prior Education	0.846	0.170

Table 8. Moderation analysis of discrete feelings on the relationship between prior knowledge and achievement.

	Estimate	SE	Z	p
Pretest * Joy	-0.0144	0.0625	-0.230	0.818
Pretest * Fun	-0.00276	0.0625	-0.0442	0.965
Pretest * Enthusiasm	3.35e-4	0.0579	0.00580	0.995
Pretest * Gratitude	0.00793	0.0651	0.1217	0.903
Pretest * Pride	0.1077	0.0616	1.750	0.080
Pretest * Awe	0.0365	0.0620	0.589	0.556
Pretest * Satisfaction	0.0367	0.0649	0.566	0.572
Pretest * Confidence	0.0345	0.0636	0.543	0.587
Pretest * Worry	0.0462	0.0726	0.636	0.525
Pretest * Frustration	0.16782	0.0897	18.707	0.061
Pretest * Nervousness	-0.0441	0.0561	-0.786	0.432
Pretest * Shame	0.1990	0.0817	2.435	0.015
Pretest * Fear	0.0559	0.0905	0.618	0.537
Pretest * Disgust	-0.1225	0.0818	-1.499	0.134
Pretest * Boredom	0.209	0.0950	2.205	0.027
Pretest * Uncertainty	-0.1466	0.0561	-2.612	0.009