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Boredom in the classroom: sentiment analysis on teaching practices and outcomes

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ABSTRACT
The present work examines the relation between teachers' teaching practices (i.e. students' evaluations of teaching and autonomy support), students' feelings of boredom, agentic engagement, and motivation. Participants were 225 university students (94 undergraduate students and 131 postgraduate students). The mean age was 26.16 (*SD* = 7.4); 78.7% women. Students' evaluations of their teachers' teaching were assessed with an open-ended questionnaire. Self-reported measures were used for the rest of the variables. To test the hypothesis relations, a structural equation model (SEM) was estimated. Results showed that boredom was negatively predicted by autonomy support practices (β = -.47) and positively predicted by negative sentiment towards teaching practices (β = .23). Results further showed a negative predictive value of boredom on students' motivation and agentic engagement (β = -.46 and −.24, respectively). This work sheds light on the influence of boredom which could help in the development of training programmes for university teachers. Altogether, results also show a promising future for sentiment analysis techniques in the field of education.

ARTICLE HISTORY

KEYWORDS
Sentiment analysis; boredom; autonomy support; motivation; agentic engagement; emotions

You are in a college lesson listening to a monotonous lecturer that has been rambling around the same topic for the last 20 min. Stuck in your seat with your unfulfilled course expectations, you find yourself constantly checking the clock only to notice how minutes slowly tick. Somehow you start to feel annoyed for time you have wasted. You just feel like a mere spectator of the current situation with no control over it. And yet, you are sat there with your eyes wandering around the room desperately needing something to happen and anxiously waiting for the lecture to be over. If you have felt identified with this situation, then you have probably suffered from boredom during your college days.

Students' emotional experiences have been a widely discussed theme among researchers, proving a central role in students' outcomes (Bieg et al., 2022; Goetz et al., 2021; Lei et al., 2018; Sutter-Brandenberger et al., 2018). Among these, academic

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boredom has shown an alarming prevalence in university students across countries (Ghensi et al., 2021; Goetz & Hall, 2014; Sharp et al., 2020) and has been linked to many detrimental outcomes in education (Ghensi et al., 2021; Grazia et al., 2021). Following both the control-value theory (Pekrun, 2006) and the self-determination theory (Ryan & Deci, 2020), researchers have placed learning environments as one of the main triggering factors of academic boredom (Daniels et al., 2015; Daschmann et al., 2011; Nett et al., 2011). Yet, up to now, far too little attention has been paid to teaching practices that prevent students' negative emotions in the higher education context, of which boredom remains relatively understudied (Ghensi et al., 2021; Sharp et al., 2021). Moreover, the assessment of learning environments in the higher education context commonly relies on students' evaluations of teaching (Baddam et al., 2019; Palmer, 2012) and is mainly dominated by self-report scales or by open-ended questions (Rybinski & Kopciuszewska, 2021). This brings two difficulties. First, self-report measures, although legitimate, are constantly questioned in terms of reliability and validity as they can bias participant responses (Paulus & Vazire, 2010). Thus, it is recommended and there is a need to rely not only on self-report measures but also complement them with qualitative data to gain a better and deeper understanding of the phenomenon under study (Johnson & Onwuegbuzie, 2004), specifically within self-determination theory research as denoted by Ryan and Deci (2020). However, analysing vast amounts of texts from written answers is a very arduous and time-consuming task that presents many complications in regard to coding. Thankfully, recent advances in natural language processing (NLP) tools can ease this task. Aimed at targeting such issues, the present study incorporates both kinds of measures and relies on one of the most popular tools in NLP to address SET: sentiment analysis (Zhou & Ye, 2020). Specifically, the present work aims to examine the relationship between teachers' teaching practices, their evaluation by students and their educational outcomes (i.e. boredom, engagement, and motivation). From a practical point of view, this approach would result beneficial to prevent boredom in higher education and improve motivation and engagement.

Academic boredom: a relevant emotion

Research on boredom is not without controversy. Still, to date, there has been little agreement on what boredom is, given that its conceptualisation varies among the fields from which it is examined (e.g. cognition, motivation, or emotion;Sharp et al., 2021). What seems less questionable is the fact that when boredom is experienced in the academic context, it can be understood as an undermining and deactivating academic emotion (Pekrun, 2006). When feeling bored, students usually feel a lack of control over the learning situation (Goetz et al., 2006), experience dissatisfaction, frustration, and a lack of interest (Vogel-Walcutt et al., 2012). Regardless of this evidence, its study in the higher education context has just begun (Sharp et al., 2020, 2021). In the available literature, the experience of academic boredom in college students has been linked to a surface approach to learning (Hemmings et al., 2019), worse performance (Eren & Coskun, 2016; Pekrun et al., 2014), dropout intentions (Respondek et al., 2017), and lower engagement (Sharp et al., 2020). For instance (Tze et al., 2014), in a sample of university students, found that feelings of boredom predicted less effort regulation and dedication. Similarly, findings from Ghensi et al. (2021) study revealed that, for those university students with higher boredom, performance was lower. With around 26–59% university students reporting feeling bored in classrooms (Sharp et al., 2020), it cannot turn out to be anything other than essential to take action.

Following the control-value theory (Pekrun, 2006), both individual (i.e. personality) and environmental factors (i.e. teaching practices (Goetz et al., 2020)) would be responsible for triggering academic emotions such as boredom. These factors shape students' cognitive appraisals of value and control. In other words, when students feel a lack of control on the learning situation and a lack of value of the learning activity, they are most likely to feel bored (Pekrun et al., 2014). Whereas individual factors (i.e. teachers' years of experience or subject knowledge) are less of a target due to their unmalleable nature, environmental factors that prevent boredom, such as teaching practices, should be under analysis. Thus, it would not only be necessary to measure students' emotions in the lectures but it should also be fundamental to link such emotions to specific teaching practices.

Autonomy support learning environments: students' outcomes

Teaching practices have been widely studied in relation to students' outcomes, positioning themselves as one of their strongest catalysts (Smith & Baik, 2019) and influencing students experiences of boredom (Bieg et al., 2022). In this sense, teachers' autonomy support has shown to have an impact on students' emotional experiences (Tze et al., 2014). A teacher that is supportive in terms of autonomy would most likely provide their students with choices, informative feedback, meaningful and explanatory rationales, and attend to their concerns and feelings, among others (León et al., 2017; Reeve, 2009). Hence, recent research has suggested the existence of three autonomy support dimensions: cognitive, procedural, and organisational (Tilga et al., 2017). Cognitive autonomy refers to encouraging students' ownership of their learning process including behaviours such as asking students to self-reflect on their learning. Procedural autonomy support would refer to encouraging students' ownership in relation to the form to approach learning. Behaviours would include offering choices to approach a task. Finally, organisational autonomy support would refer to encouraging students' ownership on the learning environment. Example behaviours would include allowing students to decide on classroom management such as classroom rules (Stefanou et al., 2004).

Contrary to this, teachers who display a controlling teaching style would ignore their students' point of view, act in an authoritarian way and pressuring students to act, feel or think in a certain manner (Reeve, 2009). These behaviours would influence students' cognitive appraisals of control and value (Pekrun, 2006; Tze et al., 2014) in such ways that not providing options would most likely give students a sense of lack of control. Moreover, not explicitly explaining why the learning content is important or useful and how it connects to real-life practices might prompt students to think the task as irrelevant and granting no value at all to the classroom content. Consistent with the self-determination theory (Ryan & Deci, 2017), this inability to internalise the value of the activity and the perceived lack of control would negatively influence students' autonomous motivation (Deci & Ryan, 2008).

Not only would this influence students' motivation but it would also predict their classroom engagement (Núñez & León, 2019). Engagement has been defined as the active involvement within the learning situations (Christenson et al., 2012). In recent years, a particular type of engagement has become more and more relevant due to its relations with students' functioning and learning (Reeve & Shin, 2020). This is agentic engagement. When students are agentically engaged, they willingly and intentionally adapt to the learning tasks to make them purposeful and relevant for themselves. Such students would most likely ask questions, express their preferences and actively contribute to the flow of lessons (Reeve et al., 2020). Consequently, students would progress and achieve higher grades (Reeve, 2013; Reeve & Tseng, 2011). Especially in the university stage, this type of engagement should result even more relevant, given that the characteristic of this educational stage seems to be conducive to it. In an environment where students willingly decide to be, where they can choose the area of expertise, they want to be more knowledgeable at, where they are responsible for their own learning and expected to work in an autonomous way (Brooks & Everett, 2008; Kyndt et al., 2015); it would seem unsurprising to expect students to be agentically engaged. However, sometimes instructors' teaching practices can deplete (or enhance) students' agentic engagement.

Attending the evidence, teachers who are autonomy supportive would enhance both students' engagement and motivation (Aelterman et al., 2019; Hospel & Galand, 2016) and negatively predict students' academic boredom (Ekatushabe et al., 2021; Tze et al., 2014). The importance of such teaching style has been supported by research. For instance, Daschmann et al. (2011) found, in a sample of secondary students, autonomy support to negatively related with students' academic boredom and positively with their engagement. Similarly, Cui et al. (2017), in a sample of college students, showed the negative predicted value that autonomy support had on students' academic boredom. Thus, evidence suggests that students experience less boredom when they have autonomy-supportive teachers (Pekrun, 2006). Nonetheless, within the self-determination theory, whereas the link between autonomy supportive practices and academic boredom is clear, not the same happens with negative emotions and autonomous kinds of motivation (Sutter-Brandenberger et al., 2018). In this way, very few studies have examined emotions as predictors of motivation (Isen & Reeve, 2005; Tam et al., 2020; Vandercammen et al., 2014) and even fewer have done so in the higher education context. This fact just highlights the need to explicitly address such links to understand the interplay of emotions, motivation, and teaching practices.

Students' evaluation of teaching: sentiment analysis approach

The higher education stage constitutes one of the most challenging and exciting phases in one's life. As described, students can choose when, where and what to study and are usually more intrinsically motivated than in earlier educational stages (Kyndt et al., 2015). Teachers become even more crucial as many students ground their decisions on which courses to enrol in based on other students' opinions and ratings of teachers. In fact, there are many repositories of student reviews on teachers available online, such as ratemyprofessors.com in the US (Rybinski & Kopciuszewska, 2021). Unfortunately, sometimes universities do not provide the personal, social and academic stimulation students demand in order to be actively engaged and motivated (Sharp et al., 2020). Perhaps because lectures are still among the most common and conventional teaching approaches in colleges (Bieg et al., 2022). This format of teaching, as opposed to autonomy supportive practices, usually entails big anonymity, low stimulation and monotony; factors strongly linked to students' boredom (Goetz & Hall, 2014).

In the higher education context, SET has become one of the main tools to assess teaching practices and their effectiveness (Cunningham et al., 2022; Palmer, 2012; Spooren et al., 2013). Results from such surveys are commonly used for decision-making relative to instructors (hiring, promotion, merit raises, etc.) and universities' publicity. They are also of great relevance for both students and teachers. For students, they encompass one of the few chances to be heard (Shah & Pabel, 2020), whereas for teachers, they comprise their almost only source of feedback (Baddam et al., 2019). Thus, understanding students' learning experiences results essential for universities to design their training courses and for teachers to improve their teaching (Palmer, 2012).

Until recently, SET studies have commonly relied on Likert scale surveys, as these are easy to collect, handle and analyse. Despite their usefulness, such method has been questioned when evaluating teaching practices (Heffernan, 2022; Spooren et al., 2013). Specifically, issues on their validity and reliability are often highlighted (for an example, see Table 1 on Rybinski & Kopciuszewska, 2021) and so, it is their mismatch with students actual learning (Uttl et al., 2017). To complement this method of collection researchers can also rely on qualitative answers from open-ended questions where students are directly asked about some aspect of the instructors' teaching to assess this. This approach provides a richer information and a better approximation to students' experiences and even causality (Maxwell, 2012; Stupans et al., 2016). However, the unstructured nature of the answers and the large amount of information obtained makes it difficult to synthesise and analyse the data, requiring an overwhelmingly intensive amount of work (Hujala et al., 2020; Shah & Pabel, 2020).

Fortunately, a systematic analysis of this kind of data is now possible. Large amounts of texts can be processed relying on sentiment analysis. This artificial intelligence-based approach obtains students' opinion from written answers and classifies them into different sentiments (positive, negative, or neutral) regarding their attitude towards their instructors teaching (Rajput et al., 2016). This approach has already proven reliable in terms of Cohen's Kappa, Fleiss' Kappa and average pairwise per cent agreement when comparing sentiment analysis results with other coders (Lin et al., 2019). Besides, other than categorising into sentiment categories, this tool also provides a numeric score on which answers represent a category. Hence, allowing its analysis

Table 1. Means, standard deviations, internal consistency and correlations among variables.

	Mean	SD	ω	1	2	3	4
1. Sentiment analysis	.16	.28	–	–			
2. Autonomy support	5.03	1.27	.93	−.45***	–		
3. Boredom	2.96	1.38	.93	−.19**	.42***	–	
4. Motivation to study	5.59	1.20	.92	−.08	.22***	.30***	–
5. Agentic engagement	4.20	1.59	.88	.24***	−.40***	−.27***	−.17*

* $p < .05$, ** $p < .01$, *** $p < .001$; $N = 225$.

from a qualitative and quantitative approach (Hujala et al., 2020). Two approaches can be followed to obtain sentiment analysis: training your own model or relying on pre-trained models. Whereas the first are considered to be more reliable, pre-trained models are less time-consuming, which could result in great advantages for applied researchers.

Sentiment analysis application in the educational context has resulted positively (Geng et al., 2020; Tseng et al., 2018; Zhou & Ye, 2020). For instance, Pong-Inwong and Songpan (2019) followed a sentiment analysis approach to examine students' feedback on their teacher's performance, concluding that it was a useful tool for teachers to adapt their teaching. Regardless of its many applications, sentiment analysis has yet to prove its relevance when it comes to assessing its relations with teaching practices and student outcomes. Whereas most research has focused on the creation of sentiment analysis models and on assessing students' satisfaction regarding teachers and courses (Zhou & Ye, 2020), to the best of our knowledge, no research before has included results from sentiment analysis into an explanatory model. This is essential, as not only is critical to assess student's satisfaction with teachers, but it is also necessary to explore how their sentiments in respect to their instructors' teaching relate with their motivation and engagement. With the present research, we aim to narrow such gap. This would help researchers better understand teaching practices and shape future interventions.

The present study

Attending the evidence just stated, research about the influence of the teaching practices on student emotions and outcomes must step forward by integrating different assessment methods and expanding the available knowledge to the higher education context. With such objective in mind, the present study aims are twofold: First, to assess how both the sentiment analysis of SET and perceived autonomy support from the teacher relates with students' experiences of academic boredom; and second, to assess the relations among academic boredom and students' motivation and agentic engagement.

Regarding the aforementioned studies showing the relation of autonomy supportive practices with students' outcomes (Ekatushabe et al., 2021; Hospel & Galand, 2016) and the relation between academic boredom and outcomes (Sharp et al., 2020), we hypothesised the following:

H_1) A negative sentiment towards teaching practices would positively predict academic boredom.

H_2) Perceived autonomy support practices would have a negative predictive value on students' academic boredom.

H_3) Students' academic boredom would negatively predict their experiences of agentic engagement and motivation to study.

Method

Participants

A total of 225 university students (Mean age = 26.16, *SD* = 7.4, 78.7% women) participated in the study. Students were enrolled in degree ($N = 94$) and master's studies

(N = 131) at the faculty of Education of a public university of Spain. The sample presented no potential ethnic differences as most of the students were Spanish.

Instruments

All items were rated according to a 7-point Likert scale ranging from *Strongly agree* (1) to *Strongly disagree* (7). In order to assess the reliability of the instruments used, McDonald's Omega was used as it has proven better accuracy in comparison with Cronbach's alpha (McNeish, 2018) and is more suitable when working with latent models. McDonalds' Omega was estimated using JASP version 0.17.2.1 (JASP Team, 2024). McDonald's Omega values are displayed in Table 1. Values ≥ .7 are indicators of good reliability (Gu et al., 2017).

Sentiment analysis

To assess students' sentiments towards their teachers' teaching, similar to previous studies (Hynninen et al., 2019), we asked them the following open-ended question: *"If you had to explain a peer who doesn't know your teacher how he or she communicates in class, what would you tell them?"*. Answering the question was necessary for students to submit their questionnaires, thus, there was no missing data. However, nine responses included a dot as an answer ("."). These were removed and left blank. Sentiment analysis was performed with Microsoft Corporation (2022) pre-trained model. This model classifies the data into a positive, neutral, or negative sentiment. For each category, the model grants a numeric sentiment score ranging from 0 to 1. The higher the score is to 1, the higher the probability of the comment belonging to such category. For this study, we relied on the probability of the students answer belonging to the negative category.

To assess the reliability of the measure, inter-rater agreement between this NLP tool and one of the researchers, who independently coded all answers, was examined. The average pairwise per cent agreement and the Cohen's kappa were calculated with ReCal2 (Freelon, 2010). The agreement reached was of 90.8% and Cohen's kappa .68, both considered satisfactory (Landis & Koch, 1977).

Autonomy support

To measure autonomy support, a short Spanish version of the Learning Climate Questionnaire (Núñez et al., 2012) was used. The scale consists of 5-items that assess autonomy support in the educational context preceded by the phrase "*In this subject*" (e.g. *"I feel very good about the way my teacher talks to me"*.). Previous works and the present study have provided evidence of reliability and validity (Behzadnia et al., 2018).

Academic boredom

To assess students' boredom, the Short-Spanish version of the Multidimensional State Boredom Scale (MSBS) was used (Alda et al., 2015). The scale consists of seven items (e.g. "*I get bored*" preceded by the stem "*In this subject*"). Previous works and the present study have provided evidence of reliability and validity (Donati et al., 2021; Oxtoby et al., 2018).

Motivation to study

To measure the motivation to study, four items (e.g. *"For the pleasure of discovering new things"*) of the intrinsic motivation towards knowledge subscale from of the Spanish version of the Échelle de Motivation en Éducation (Núñez et al., 2005) were used. Items were preceded by the stem "Why do you study?". Previous works and the present study have provided evidence of reliability and validity (León et al., 2015).

Agentic engagement

Students' agentic engagement was measured using the 4-item subscale of the Classroom Engagement Scale (Núñez & León, 2019). Items (e.g. "*I try very hard to do well in this subject*") were preceded by the stem "*In this subject*". Previous works and the present have provided evidence of reliability (Froment & de Besa Gutiérrez, 2022).

Procedure

Data collection took place during the first and second semesters of the 2021–2022 academic year when the course students were enrolled were about to end. Data was collected using an online questionnaire students could access through a QR code they completed during a teaching period where the assessed teacher was not present. The objectives of the study were explained to all students, highlighting the voluntary and confidential nature of their participation. Returned questionnaires were interpreted as informed consent. Participants were explained with their right to withdraw at any time from the study without any consequences. Answers to items were made mandatory in order for participants to submit their answers, hence there was no missing data on the self-report measures. The study was conducted in accordance with the ethical guidelines of the Declaration of Helsinki and was approved by the University Human Research Ethics Committee.

Data analysis

To test the hypothesis relations a structural equation model (SEM) was estimated. Model fit information was identified from the following fit indices: the root mean square error of approximation (RMSEA), standardised root means square residual (SRMR), comparative fit index (CFI) and the Tucker–Lewis index (TLI). A model has a good fit when $\chi^2/\text{df} < 5$, RMSEA values are < .08, SRMR values < .06 and CFI/TLI values > .95 (Hu & Bentler, 1999). Yet, these indices should be interpreted with some flexibleness when working with naturalistic data (Heene et al., 2011). 95% confidence intervals (CIs) were estimated around the beta coefficient. CIs are statistically significant at $p < .05$ when they do not cross.

Students were nested within their respective classes. Given the categorical nature of the variables, the weighted least square mean adjusted estimator (WLSM) was used as the estimation method. This estimator was also chosen due to its higher accuracy over the maximum likelihood method when working with categorical variables that are not normally distributed (Schmitt, 2011).

To account for homogeneity of the data, we tested if they were differences between degree and master's students on the answering of items by comparing various models:

Table 2. Model fit indices to assess differences across enrolment status.

Model	χ^2	*df*	*p*	RMSEA	CFI
Model 1	562.350	92	.000	.091	.905
Model 2	575.089	111	.000	.088	.920
Model 3	649.533	96	.000	.095	.902
Model 4	664.590	92	.000	.096	.899
Model 5	724.559	88	.000	.103	.882

a model with unconstrained loadings, thresholds and means; a model with factor loadings constrained to be the same across enrolment status, thresholds and means unconstrained; a model with loadings and thresholds constrained and means unconstrained; and finally a model with loadings, thresholds and means constrained. For model comparisons, we relied on changes in CFI and RMSEA (Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). All data analysis was performed with M*plus 8.4* (Muthén & Muthén, 1998–2024). Missing data (nine responses for the question on sentiment analysis left blank) were handled with the full information maximum likelihood approach. Following (Keith, 2019), the magnitude of standardised beta coefficients with a value > .05 are considered small, > .10 moderate, and > .25 as large.

Results

Preliminary analyses

Descriptive statistic, McDonald's Omega and Pearsons' correlations among variables are displayed in Table 1. For factor loadings, see the supplementary material. These were all above .74.

Multiple-group analyses were conducted to examine potential differences among enrolment status (grades vs. master's students) in model results. According to comparisons in model fit information (CFI and RMSEA), results show minimal differences among fit indices suggesting no differences across grade and master's students' samples (Table 2).

Structural equation models

Model fit indices for the estimated model showed a good fit to the data; χ^2 (134) = 351.129, $p < .001$, RMSEA = .07, TLI = .91, CFI = .92 except for SRMR = .09. Figure 1 displays the standardised parameters for the relations among variables.

All paths resulted in a statistically significant $p < .05$ and relations among variables showed a moderate to large magnitude. Regarding the nature of the relations, results showed that autonomy support from the teachers related negatively with students' boredom, whereas a negative sentiment towards teachers' teaching practices related positively with students' boredom. Regarding the relation between boredom and motivation, results showed a negative relation. Hence, feeling bored in the classroom negatively predicted student's motivation. Finally, students' boredom also related negatively with students' agentic engagement.

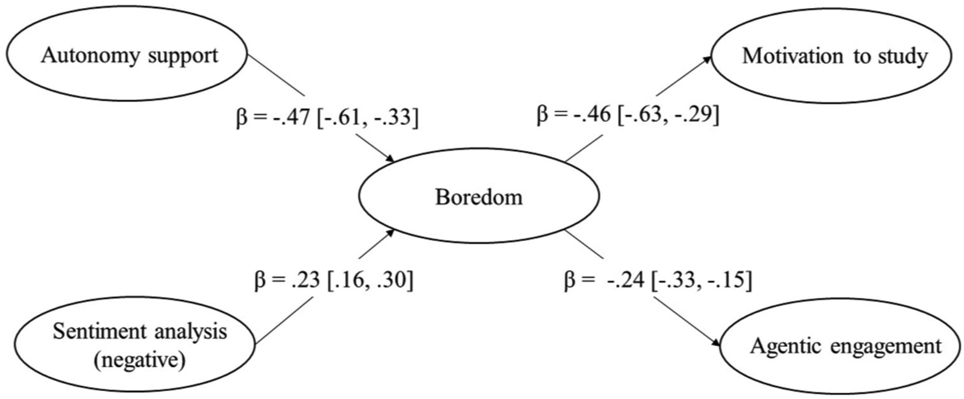

Figure 1. Standardized regressions with 95% confidence interval between square brackets

Discussion

The current research had two goals. First, to examine how both the sentiment analysis from SET and perceived teacher autonomy support related with students' experiences of boredom. Second, to examine relations among boredom and students' motivation to study and agentic engagement. Results indicate that, as expected, autonomy supportive practices relate negatively with students' academic boredom, whereas for the negative sentiment analysis, this relation is positive. Regarding motivation to study and agentic engagement, both outcomes are negatively predicted by academic boredom. Altogether, results show a promising future for sentiment analysis techniques in the field of education as they prove the usefulness of this tool when evaluating relations between teaching practices and student outcomes. Major findings are discussed below.

Students' evaluation of teaching: sentiment analysis

Regarding H_1 as expected, a negative sentiment towards teaching practices positively predicts academic boredom. In other words, when students' opinion towards their instructors' teaching practices is negative, it is more likely for them to feel bored. This finding, once again, highlights the importance of emotions in the learning context and lines up with previous findings linking teaching practices, such as displaying humour and enthusiasm, and student's emotions, such as enjoyment and boredom (Bieg et al., 2022; Cui et al., 2017). Moreover, it adds on such relation by not addressing and classifying general emotions but rather by addressing student's actual opinion on teachers teaching and extracting its valence. As such, the present finding highlights and strengthen the idea of the power teachers have to get them involved and engaged in the classroom, but also the influence they have to achieve the exact opposite. In a context where most students report feeling bored (Ghensi et al., 2021; Sharp et al., 2020), this finding is of special relevance for teachers, as it emphasises the pertinence to attend their teaching practices and the way they approach students in the higher education context.

Results also proved the reliability and validity of sentiment analysis as a tool to address feedback from students. With a 90.8% of agreement and a Cohen's kappa of .68, results show a substantial agreement between the tool and researchers (Landis & Koch, 1977). Nevertheless, Cohen's kappa not reaching the widely accepted threshold of .70 could be due to the overrepresentation of some categories (the category positive was coded around 60–70% of cases, whereas neutral and negative category around 10–20% (Feinstein & Cicchetti, 1990).; This finding is in line with previous works that incorporate sentiment analysis to evaluate teachers' teaching practices (Geng et al., 2020; Tseng et al., 2018). Hence, findings highlight how valuable information obtain from students' answers to open-ended questions can serve and help in the understanding on how teacher behaviours relate with student's classroom experiences relying on AI-based tools. Nonetheless, the present work aims to innovate and to take a step forward by incorporating sentiment analysis into an explanatory structural equation model which, to the best of our knowledge, has not been done before. Thus, the results present a promising way of integrating sentiment analysis of SET within structural equation models to test hypothesised relations and not only explore students' satisfactions with teachers. Autonomy supportive practices, boredom, motivation, and engagement

In respect with H2, evidence gathered confirms such hypothesis. In such a way, in line with the SDT and CVT postulates (Pekrun, 2006; Ryan & Deci, 2017) and similar to previous studies (Tze et al., 2014) students' perceived autonomy support negatively predicts students' boredom. For instance, Ekatushabe et al. (2021) found in a sample of secondary students, that when teachers were perceived as autonomy supportive, students reported less boredom, whereas Tze et al. (2014) found the same in a sample of university students. Such finding highlights the critical role of autonomy supportive practices to mitigate students' boredom. University teachers should therefore try to move away from a classic lecturer format where content is just listed, and students barely interact or participate. Instead, given the importance of control and value appraisals as antecedents of students' boredom (Pekrun, 2006) and motivational experiences (Ryan & Deci, 2017), teachers could remark the value of the learning content for students' life's and grant them with chances to be agents of their own learning. Teachers who can do so, would have students who experience less academic boredom. Given the negative impact boredom has on students (Ghensi et al., 2021; Grazia et al., 2021), this should be an overriding objective of the higher education stage, especially if we consider the differences in instruction practices within secondary levels and the university level where lectures are the most common teaching approach (Bieg et al., 2022). In this sense, the present findings, and previous ones (Ekatushabe et al., 2021) highlight how effective teaching practices are crucial throughout educational levels. Therefore, university teacher roles extend beyond imparting knowledge to fostering critical thinking, analytical skills, and a deep understanding of the subject matter. As Stefanou et al. (2004) and Tilga et al. (2017) remark, university teachers could therefore be autonomy supportive in terms of organisation, procedure, and cognitions by encouraging students' ownership of the learning environment, the learning approach, and the learning process. Offering choices on classroom management decisions (e.g. examination dates, classroom rules, etc.), providing the freedom to present coursework in the preferred format or encouraging discussions and justifications on students points and ideas would most likely enhance students learning and classroom experiences.

Finally, results also support H3. Students' academic boredom negatively predicted students' experiences of agentic engagement and motivation. This lines up with Tam et al. (2020) results which found, in a sample of secondary students, that their feelings of boredom reduced their learning motivation. Similarly, Sutter-Brandenberger et al. (2018), also, in a sample of secondary students, found negative relations between boredom and motivation. Our findings, thus, expand previous results by demonstrating the link between boredom and intrinsic motivation in the higher education context. Regarding the links between academic boredom and agentic engagement, previous works have highlighted the link between boredom and behavioural, cognitive, and emotional engagement (Tze et al., 2014; Wang et al., 2017). However, to the best of our knowledge, these are the first results to highlight the link between agentic engagement and boredom in the higher education context, and thus could not be discussed with previous findings. Nevertheless, results suggest that if students feel boredom in the classroom, and then it is less likely that they would try to find, intentionally, the utility of such tasks and actively contribute to the learning process taking place in the classroom. In this sense, teachers have a lot to say and do. For instance, Reeve et al. (2020) and Cheon and Reeve (2015) trained teachers to be autonomy supportive and found gains in students' agentic engagement and motivation.

Limitations and future directions

The present study contributions are not exempt from limitations. First, despite integrating different assessment methods, part of the present work relies on self-reported scales which come with some bias (Paulus & Vazire, 2010). Future research could complement these measures with observational techniques regarding teaching practices, teacher self-reports measures or even behavioural indicators of emotions and attentional states (facial recognition of emotions, students' yawning, looking at the clock/phone, eye-tracking monitoring). Second, the data were cross-sectional. Similar to previous research (Bieg et al., 2022), future research could collect different data points during each lecture. This would help to observe whether changes in teaching practices predict changes in student outcomes. Future works could also contemplate conducting experimental research to properly assume causation among variables examined. Third, a relatively small sample in a model with several indicators can increase the likelihood of overfitting the model, leading to findings that may not generalise to larger populations, and future research should aim to replicate the study with larger samples to validate the findings and enhance the robustness of the model. Furthermore, alternative analytical methods or the use of cross-validation techniques could be considered to verify the stability and reliability of the results obtained from the SEM analysis with less indicators tested. Moreover, such sample sizes also constrain the exploration of more complex relations among the variables. For instance, with a higher sample size of classes, future researchers can replicate the present study following a multilevel design (Zitzmann et al., 2022). This would help researchers to identify features of the classroom climate (i.e. class-level variables such as teaching quality) that relate with students' outcomes (i.e. student-level variables such as boredom). Fourth, open-ended questions, although being a rich source of information, can also come with potential bias towards the positive evaluation of teaching observed also in sentiment analysis studies (Alhija & Fresko, 2009; Cunningham-Nelson et al., 2019; Hynninen et al., 2020; Sengkey et al., 2019). This can be mitigated by formulating open-ended questions in a way which leaves no room for vague, general, simple, or sarcastic answers. Future research could extend the present research by incorporating more measures on different emotions such as hopelessness or anger. This could assist a better understanding on how teaching practices can relate with different aspects of student's negative emotional experiences. Future research could also benefit from incorporating positive emotional experiences as well as the negative, to properly examine the interplay of both. Finally, it would be interesting for subsequent research to include other SET data, so that the distinctive contribution of SE to the outcomes assessed (e.g. boredom, motivation and engagement) could be analysed.

Practical implications for teaching

Considering the impact autonomy supportive teaching practices have on students' outcomes, the present findings could be of relevance for teachers and policymakers, to tackle boredom in the university. As previous findings highlight (Ahmadi et al., 2023), increasing students' intrinsic motivation through teachers' support of their basic psychological needs could be a way to address students' boredom. In their work, Ahmadi et al. (2023) highlight several teaching behaviours that teachers can incorporate into their teaching to support their students' needs leading to a more engaging learning environment. Such knowledge could be incorporated into training programmes for university teachers and equip them with the right tools for such purposes. As so, the AI-based sentiment analysis tool can also be incorporated into day-to-day practice by teachers as a self-assessment method. Real-time analysis of student sentiments can provide valuable insights, allowing instructors to make timely adjustments and create a more positive learning experience while encouraging a culture of continuous improvement. Ultimately, the information collected could also be utilised to support and strengthen the capabilities of educators. Teachers that are confident in achieving positive educational results, this is a high self-efficacy, have higher chances of positively influencing students' learning experiences (Daumiller et al., 2021). Thus, recognising and emphasising to teachers the power they have to tackle boredom in the classroom can boost their sense of self-efficacy, ultimately empowering their teaching efforts.

Conclusion

Taken altogether, the present research presents an innovative approach to incorporate a natural language processing tool onto the study of students' evaluations of teaching. By doing so, and complementing it with self-report measures, we account for the arduous task of coding such amount of data. Not only it brings methodological benefits for the research community, but the present results can also help the university community. Attending the negative repercussions boredom brings (Camacho-Morles et al., 2021; Ghensi et al., 2021; Goetz & Hall, 2014; Grazia et al., 2021; Nett et al., 2011;

Pekrun et al., 2014), trying to mitigate the appearance of this emotion in the classroom should shape instructors' teaching practices. As a practical implication, the present findings could help the development of future training programmes for university teachers on how to deliver an autonomy supportive teaching and how to cultivate students' intrinsic motivation.

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