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The Georgia School Personnel Survey of school climate: Validity evidence from a sample of Portuguese teachers and support staff

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Abstract

This study focuses on the adaptation of the Georgia School Personnel Survey (GSPS) to assess perceptions of school climate among Portuguese educational professionals, including teachers and support staff. Data from two samples ($n_1 = 1965$; $n_2 = 2884$) were analysed in the study. Through confirmatory factor analysis, the survey's structure was validated, revealing a second-order factor composed of six first-order dimensions. The adapted version of the GSPS exhibited high internal consistency, affirming its stability across diverse occupational and gender groups. The instrument revealed measurement invariance, ensuring its appropriateness for comparative analysis across different demographic groups. The validity evidence of the GSPS was rigorously tested through its relationships with related constructs. It demonstrated large positive correlations with job satisfaction and work engagement, and a large negative correlation with burnout, highlighting its role within the nomological network of constructs related to school climate. The results support the use of GSPS as a tool for assessing school climate within Portuguese school settings, providing key insights for school improvement initiatives. The study underscores the importance of accurate measurement of school climate to enhance

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the understanding of its impact on school personnel. By providing a tool with strong validity evidence, this research contributes to the ongoing efforts to improve school environments, which is fundamental for fostering staff well-being and enhancing institutional effectiveness.

KEYWORDS
Georgia School Personnel Survey (GSPS), school climate, school personnel, validity evidence

Key insights

What is the main issue that the paper addresses?

The paper addresses the adaptation of the Georgia School Personnel Survey (GSPS) to assess school climate perceptions among Portuguese educational professionals, including teachers and support staff.

What are the main insights that the paper provides?

The adapted GSPS demonstrated strong validity evidence for assessing school climate in Portuguese settings. It exhibited measurement invariance across occupational groups and gender, and showed meaningful associations with job satisfaction, burnout, and work engagement.

INTRODUCTION

School climate is a complex, multidimensional construct that reflects a school's quality through its members' collective experiences and perceptions (Bear et al., 2017; Cohen et al., 2009; Mitchell et al., 2010; National School Climate Center, 2007; Thapa et al., 2013). Although the features deemed important for such appraisals may vary across cultures (Shukla et al., 2019; Yang et al., 2013), stakeholder groups (Capp et al., 2021; You et al., 2014) and individual groups (Kutsyuruba et al., 2015; La Salle, McCoach, et al., 2021), they are generally grouped within the literature under four domains: academic climate, interpersonal relationships, safety and institutional environment (Te Wang & Degol, 2016), which together provide a comprehensive framework for evaluating school climate.

Interest in school climate has surged as research demonstrates that students' positive perceptions of their school environments can significantly enhance both academic performance and developmental outcomes. A review by Aldridge and McChesney (2018) analysed 48 studies, mostly correlational, linking school climate perceptions to student mental health. The findings indicated that a positive school climate correlates with better well-being, resilience and coping, while inversely relating to mental health issues such as psychopathology and emotional or behavioural problems. Academically, a meta-analysis of 37 studies found that positive school climate perceptions are associated with improved academic achievement, showing a medium effect size (Erdem & Kaya, 2024). Additionally, other studies have connected positive school climate perceptions with decreased absenteeism (Hamlin, 2021; Van Eck et al., 2017). Moreover, a bibliometric analysis by Obeidat et al. (2024) highlighted the growing body of literature emphasising the link between school climate and student well-being. This analysis identified several key themes, including the importance of supportive teacher–student relationships, a safe and inclusive environment, and the role of school climate in fostering students' sense of belonging and overall psychological well-being.

While extensive research has explored student perceptions of school climate and their positive outcomes, fewer studies have examined this from the perspectives of other school members like teachers and support staff (Capp et al., 2020b). However, recent research mirrors findings from student samples, showing that teachers' positive views of school climate are also associated with beneficial outcomes (Gonzálvez et al., 2022; Grazia & Molinari, 2021; Saint et al., 2021). For instance, studies indicate that positive perceptions of school climate among teachers are linked to increased job satisfaction, self-efficacy, well-being, as well as reduced stress and burnout (Aldridge & Fraser, 2016; Collie et al., 2012; Grayson & Alvarez, 2008; Malinen & Savolainen, 2016; Zakariya, 2020). These perceptions are also associated with greater teacher commitment (Collie et al., 2011) and implementation fidelity of new curricula and interventions (Beets et al., 2008; Gregory et al., 2007). Additionally, teachers' positive perceptions of the school climate are linked to improved student academic achievement, indicating important trickle-down effects (Back et al., 2016; Bear et al., 2014).

Measuring the perceptions of teachers and other school personnel

Multilevel studies show that perceptions of school climate significantly predict school personnel burnout, including average levels and changes over time, while school-level factors alone are often less significant (O'Brennan et al., 2017; Pas et al., 2012). These findings highlight the importance of understanding school personnel's perceptions over school-level factors when addressing challenges within the school setting. Research also indicates that different types of school professionals have varying perceptions of school climate (Capp et al., 2020b). Therefore, measures of school climate must include the perspectives of all school personnel — not just teachers — but also school psychologists, social workers, certified professionals and classified staff like secretaries, custodians, and cafeteria workers. Each group contributes to the school climate and experiences outcomes, such as burnout, affecting the school environment (Capp et al., 2020a). Incorporating these diverse perspectives ensures a comprehensive understanding of the school climate, ultimately supporting the well-being and effectiveness of the entire school community.

To that end, several measures have been developed to assess school climate from the perspectives of different stakeholders, including teachers, staff, and families. As identified in the recent systematic review by Gonzálvez et al. (2022), these measures include: the Delaware School Climate Survey — Teacher/Staff (Bear et al., 2014); the teacher version of the Authoritative School Climate Survey (Huang et al., 2015); the Programme for International Student Assessment (PISA) 2009 School Climate Scale (Sun & Royal, 2017); the School Climate Scale for Primary School Teachers (Anwar & Anis-ul-Haque, 2014); the Inclusive School Climate Scale (Emam & Al-Mahdy, 2022); the School Climate Questionnaire for Secondary and High School Teachers (Domínguez et al., 2019); and the School Climate Scale developed through a user experience approach (Sudla et al., 2020). Other multi-informant assessment batteries, while not identified by Gonzálvez et al. (2022) but still relevant, include the Comprehensive School Climate Inventory (National School Climate

Center, 2002), the School Climate Assessment Instruments (Alliance for the Study of School Climate, 2004), the California School Climate, Health, and Learning Survey System (WestEd, 2014) and the Georgia School Climate Survey (GSCS) (La Salle et al., 2018). An analysis of these measures confirms that even when similar factors are evaluated, researchers often label these dimensions differently across studies, even if the items themselves are similar (Grazia & Molinari, 2021; Shukla et al., 2019). Nonetheless, multidimensional school climate measures are particularly valuable because they allow researchers and schools to clearly identify areas of strength as well as aspects requiring intervention or improvement, providing targeted information necessary to link specific school climate dimensions to student and school staff outcomes (Lewno-Dumdie et al., 2020).

The Georgia School Personnel Survey

Developed by the Georgia Department of Education under the leadership of Tamika La Salle-Finley, the GSCS (La Salle et al., 2018) evaluates perceptions of students (grades 3–5 and 6–12), school staff, and families regarding school climate across all four dimensions described by Te Wang and Degol (2016). Compared to similar measures, the GSCS is among the shortest, reducing respondent burden and potentially increasing participation rates across all categories of school personnel. Despite it brevity the GSPS presents good psychometric properties. Moreover, the GSCS uses a multi-informant approach, capturing and integrating diverse perspectives from key stakeholders, thereby offering a more comprehensive and accurate portrayal of the school climate (Marraccini et al., 2020). Another important feature of the GSCS is that it is offered free of cost, ensuring wider accessibility and usability for schools, thus reducing resource inequalities—an important factor in social justice (Baumsteiger et al., 2023). Collectively, these strengths make the GSCS a valuable tool for schools seeking to assess the school climate in an efficient, continuous, and sustainable manner, making it particularly suitable for informing school improvement efforts.

The school staff component of the GSCS, known as the Georgia School Personnel Survey (GSPS), has not yet been adapted outside the state of Georgia in the United States of America. Psychometric evidence is limited to a single study involving 167,000 Georgia school personnel who completed the 31-item GSPS (Saint et al., 2021). This study demonstrated the scale's validity evidence across various genders, racial/ethnic identities, grade levels and occupational groups. Although these findings suggest that the GSPS is useful for assessing school climate perceptions among diverse school staff, further adaptation studies in broader contexts are needed.

Present study

This study is part of the International School Climate Collaborative (ISCC), a research group dedicated to the cultural adaptation of the GSCS (Di Sano et al., 2024), which emerged from the International School Psychology Association Research (La Salle, Rocha-Neves, et al., 2021). Since no studies have yet adapted the GSPS for Portugal, this study aims to adapt the GSPS for European Portuguese. This effort aligns with the ISCC's goal of developing school climate surveys for diverse linguistic and cultural contexts and further examining differences in how school climate is perceived across countries.

Following the guidelines of the *Standards for Educational and Psychological Testing* (American Educational Research Association, 2014), this study will assess two key sources of validity evidence for the GSPS: one related to its internal structure and the other based on its relationships with other variables. To provide validity evidence based on the internal structure, three hypotheses were tested. Hypothesis 1 proposes that the GSPS retains its original dimensionality, consisting of one second-order factor with six first-order dimensions and 29 items. Hypothesis 2 posits that the GSPS demonstrates satisfactory reliability. Hypothesis 3 asserts that the GSPS maintains measurement invariance across occupational groups (teachers and support staff) and gender (female and male), ensuring it assesses the construct uniformly, which is crucial for concluding that statistical differences represent real differences in the construct (Saint et al., 2021).

The second source of validity evidence, based on relationships between GSPS scores and external variables, will be assessed using measures of job satisfaction, burnout, work engagement and years of professional experience in the current role.

Job satisfaction

Job satisfaction among school staff has been empirically linked to perceptions of the school climate. A positive school climate often correlates with higher job satisfaction by fostering a supportive and collaborative work environment (Thapa et al., 2013). Studies have indicated that when teachers perceive their school climate as inclusive and safe, they report greater satisfaction with their roles (Grayson & Alvarez, 2008). Additionally, research has also shown a direct effect of school climate on job satisfaction (Aldridge & Fraser, 2016; Malinen & Savolainen, 2016; Otrębski, 2022; Zakariya, 2020).

Burnout

Burnout among educators is also significantly influenced by the climate of the school environment. Negative aspects of school climate — such as disorder, lack of resources, ineffective leadership, and poor classroom relational climate — have been associated with higher levels of teacher burnout (Alamos et al., 2022; Arens & Morin, 2016). Conversely, a supportive school climate can act as a buffer against the stress that often leads to burnout among both students and teachers (Fatou & Kubiszewski, 2018; Grayson & Alvarez, 2008).

Work engagement

Similarly, work engagement in educational settings is related to the perceived school climate. A nurturing and supportive school climate fosters greater work engagement by providing a sense of belonging and professional efficacy (Klassen et al., 2010). Positive school climates that promote teacher autonomy and involve teachers in decision-making processes have been shown to enhance work engagement, thereby improving overall job performance and satisfaction (Skaalvik & Skaalvik, 2014).

Finally, research supports a relationship between the length of tenure among school staff and their perceptions of school climate. The results show that educators who work in positive school climates are more likely to remain at their schools longer, compared to those who experience adverse climates, marked by conflict and lack of support (Boyd et al., 2011). A stable and positive school climate can reduce staff turnover by increasing job satisfaction, and fostering a stronger commitment to the school (Ingersoll, 2001).

As such, Hypothesis 4 assumes that GSPS presents convergent evidence with job satisfaction, burnout, work engagement, and tenure time.

METHOD

Sampling

The minimum required sample size for the model was estimated with the assumption that the population root mean square error of approximation (RMSEA) should not exceed $\varepsilon_0 = 0.06$ (H_0: $\varepsilon \geq 0.06$). Rejecting this hypothesis would indicate that the model fit is better than 0.06, which is the recommended threshold for a good fit (Hu & Bentler, 1999). Furthermore, the true population RMSEA was set at $\varepsilon = 0.05$ based on previous research using the instrument (Saint et al., 2021). Using a significance level of $\alpha = 0.05$ and a power (π) of 0.8 ($\beta = 0.2$), the required minimum sample size was determined to be $n = 272$ (Kelley & Lai, 2018).

Psychometric instruments and demographic data

Demographic and professional survey

The GSPS contains predefined demographic questions and response categories, which were adapted to fit the Portuguese context. In this study, a general questionnaire was used to collect sociodemographic information, including gender, age, highest degree earned, primary role, years of professional experience, and tenure at the current school, among other variables.

Georgia School Personnel Survey

The GSPS measures staff perceptions of school climate across six subscales using a 29-item survey with a four-point rating scale from ‘strongly disagree’ (1) to ‘strongly agree’ (4), including one reverse-coded item (item 14). These subscales cover key dimensions of the school climate: (a) staff connectedness (items 1–6) assesses how integrated staff feel within the school community (e.g., ‘I get along well with other staff members at my school’); (b) structure for learning (items 7–12) evaluates perceptions of clarity in expectations, fairness in student treatment, and academic standards (e.g., ‘Teachers at my school have high standards for achievement’); (c) school safety (items 13–16) measures perceptions of safety on school premises (e.g., ‘I feel safe at my school’); (d) physical environment (items 17–20) captures views on the maintenance and adequacy of school facilities (e.g., ‘My school building is well maintained’); (e) peer/adult relations (items 21–26) evaluates interactions between students and adults (e.g., ‘Students at my school get along well with one another’); and (f) parental involvement (items 27–29) assesses the extent of parental involvement in education (e.g., ‘Parents at this school frequently attend school activities’). The GSPS aims to gather comprehensive data on school climate and deepen the understanding of its dimensions. Higher scores in the GSPS reflect more positive perceptions of school climate, as seen in both total and subscale scores (La Salle et al., 2018).

Transcultural adaptation

The translation of the GSPS from English to Portuguese followed the second edition of the *ITC Guidelines for Translating and Adapting Tests* (International Test Commission, 2018). A bilingual research team member, proficient in both European Portuguese and English and with a deep understanding of the Portuguese educational system, conducted the initial translation. This translation was reviewed by two additional team members, and their feedback was used to create a unified preliminary version. This version was then sent to the main research team, where another bilingual member performed a back-translation into English. Since the original and back-translated versions were similar, no modifications were necessary. The translation was subsequently reviewed by six teachers, two operational assistants and two school psychologists to assess content validity. These individuals evaluated the clarity and cultural appropriateness of the language used in the items. Their suggestions were incorporated into the final Portuguese version, which was used in the first round of data collection. Based on participant feedback and statistical analysis from this first round, the questionnaire was revised for a second round of data collection. The main changes included replacing 'teachers' with 'professionals' in items 1, 6, 19 and 20 to better reflect the roles of various staff members, recognising that the GSPS is completed by all school staff, not just teachers. Minor changes for clarity involved simplifying terms and wording to enhance readability and comprehension in items 12, 14, 15, 17 and 26.

Utrecht Work Engagement Scale

We evaluated participant work engagement using the short version of the Utrecht Work Engagement Scale (UWES-9) (Sinval, Marques-Pinto et al., 2018; Sinval, Pasian et al., 2018). The UWES-9 comprises nine items that measure work engagement as a second-order construct with three theoretical dimensions of engagement (first-order factors): vigour, dedication and absorption. Participants rated each item on a scale from 'never' (0) to 'always' (6), where higher scores indicate greater work engagement. Studies conducted specifically with Portuguese samples have confirmed the psychometric adequacy of the UWES-9 (e.g., Sinval, Marques-Pinto et al., 2018).

Burnout Assessment Tool

We measured burnout using the 12-item version of the Burnout Assessment Tool (BAT-12) (Sinval et al., 2022), which has been adapted for the population of workers in Portugal. The BAT-12 measures burnout as a second-order factor, capturing four core symptoms of burnout (first-order dimensions): exhaustion, mental distance, cognitive impairment and emotional impairment. Participants are requested to rate each item based on how much it applies to their work situation, using a five-point scale ranging from 'never' (1) to 'always' (5).

Short Index of Job Satisfaction

To measure job satisfaction, we used the five-item shortened version of the Index of Job Satisfaction (Brayfield & Rothe, 1951). This scale asks participants to respond to statements about their job satisfaction, such as 'I feel fairly satisfied with my present job', on a scale from 'strongly disagree' (1) to 'undecided' (3) to 'strongly agree' (5). After reverse-coding two negatively worded items, higher scores indicate greater job satisfaction. A psychometric study of the Portuguese and Brazilian versions of this scale confirmed its unidimensional structure and demonstrated good validity evidence ($\omega_{\text{Portugal}} = 0.90$) (Sinval & Marôco, 2020).

Procedures

This study was approved by the Ethics Committee of Universidades Lusíada (JL/CE/CIPD/2303). The first author recruited participants through their established network of public-school contacts. The research proposal was presented to each school's board for approval by the pedagogical council. At each participating school, professionals completed self-report questionnaires via the LimeSurvey (LimeSurvey GmbH, 2024). The survey link was distributed by the school administration through institutional email. The survey's initial webpage provided comprehensive study information, including digital informed consent, which was actively provided via a click in a checkbox, and emphasised the voluntary and confidential nature of participation. Participants completed the questionnaires between March and June 2023 (first data collection), and March and June 2024 (second data collection) academic years. Data collection occurred within a 1-month period at each school, covering 23 school clusters in 2022/2023 and expanding to 30 in 2023/2024. For the purposes of analysis, only responses that were fully completed were recorded. At the end of each data collection period, schools received detailed reports of their results, along with support for data analysis and reflection, to facilitate incorporating findings into school action plans.

Data analysis

Statistical analysis was conducted using R (R Core Team, 2024) via RStudio (Posit Team, 2024). Descriptive statistics were generated with the skimr (McNamara et al., 2021), PerformanceAnalytics (Peterson & Carl, 2020), sjstats (Lüdecke, 2021), plotrix (Lemon, 2006), and modeest (Poncet, 2019) packages.

We conducted confirmatory factor analysis (CFA) to evaluate the originally proposed dimensionality of the scale. The following goodness-of-fit indices were used: CFI (comparative fit index), TLI (Tucker–Lewis index), NFI (normed fit index), RMSEA and SRMR (standardised root mean square residual). CFI, NFI and TLI values above 0.95 are considered good, while SRMR and RMSEA values below 0.08 are expected (Browne & Cudeck, 1993; Hu & Bentler, 1999). The minimum sample size for CFA was estimated using the MBESS package (Kelley, 2023). CFA was performed with the lavaan package (Rosseel, 2012) using the weighted least squares means and variances (WLSMV) estimator, which is suitable for categorical indicators and does not require the assumption of multivariate normality (Muthén, 1983).

A multidimensional polytomous Rasch model (Briggs & Wilson, 2003) was employed for item response theory (IRT) analysis using the TAM package (Robitzsch et al., 2021) to implement the multidimensional random coefficients multinomial logit model (MRCMLM) by Adams et al. (1997). The item-person map (Wright map) was generated via the WrightMap package (Irribarra & Freund, 2020). Infit and outfit mean square fit statistics were evaluated for each item (Linacre, 2002), with acceptable values for rating scales ranging from 0.6 to 1.4 (Bond et al., 2020). Rasch analysis provided detailed insights into item properties related to difficulty and coverage of the latent trait (θ).

To assess the reliability of the first-order factors, we used the following internal consistency estimates: α_{ordinal} (Green & Yang, 2009), ω (McDonald, 1999) and average variance extracted (AVE) (Fornell & Larcker, 1981). Values of α_{ordinal} and $\omega \geq 0.7$ indicate acceptable reliability, while AVE values ≥ 0.5 are considered satisfactory (Hair et al., 2019). These estimates were calculated using the semTools package (Jorgensen et al., 2023).

The expected a posteriori (EAP) reliability index from the MRCMLM was estimated to measure the precision of the estimation of latent factor. Defined as the ratio of EAP variance to plausible values variance (Adams, 2005), EAP values ≥ 0.8 are considered preferable.

Measurement invariance for the second-order model with categorical indicators was assessed via theta parameterisation using the semTools package (Jorgensen et al., 2023). Eight nested models with varying constraints were compared (Millsap & Yun-Tein, 2004), employing the ΔCFI ≤ -0.010 criterion (Cheung & Rensvold, 2002) and the $\Delta\chi^2$ criterion (Satorra & Bentler, 2001).

The lavaan package (Rosseel, 2012) was used to fit the structural model, correlating all convergent variables with school climate to assess validity evidence based on relations to other variables. The diagrams were produced using the semPlot package (Epskamp, 2015) and the semptools package (Cheung & Lai, 2023). All statistical analyses were performed with $\alpha = 0.05$.

RESULTS

Sample characterisation

We analysed two large samples of education professionals from Portuguese public and private schools. Sample 1 comprised 1965 participants who completed the GSPS during the 2022/2023 school year. Sample 2 comprised 2884 participants who completed the GSPS during the subsequent school year. It is important to note that some schools participated in both data collections, which means that participants from these schools may have responded in both the 2023 and 2024 surveys; consequently, the samples will not be merged due to their potential overlap. Table 1 outlines their characteristics. The 2023 sample included 1634 females, 285 males and 46 non-binary individuals, an average age of 50.3 years, with most (72.1%) being teachers with nearly 10 years of experience and 77.4% holding higher education degrees. The 2024 sample, comprising 2449 females, 408 males and 27 non-binary individuals, showed a similar average age and consisted of 69.3% teachers, who averaged 10.7 years of experience and 71.8% had higher education.

Validity evidence based on the internal structure

The distributional properties of GSPS items are presented in Table 2. None of the items presented $|ku| \geq 7$ or $|sk| \geq 3$, suggesting the absence of severe violations of univariate normality (Finney & DiStefano, 2013; Marôco, 2021).

Dimensionality

The CFA that tested the original dimensionality of the GSPS with the 2023 sample presented a satisfactory fit to the data ($\chi^2_{(371)} = 4169.26$; $p < 0.001$; CFI = 0.96; TLI = 0.95; NFI = 0.95; SRMR = 0.07; RMSEA = 0.07; $p_{(\text{RMSEA} \leq 0.05)} < 0.001$; 90% CI (0.07, 0.07)). However, a very low factor loading was detected for item 14, 'I have been concerned about my physical safety at school' ($\hat{\lambda}_{\text{item 14}} = 0.184$). After an inspection of item 14's content, the item was removed, and a CFA was conducted to analyse the modified model. The reduced model presented a good fit to the data ($\chi^2_{(344)} = 3669.61$; $p < 0.001$; CFI = 0.96; TLI = 0.96; NFI = 0.96; SRMR = 0.06; RMSEA = 0.07; $p_{(\text{RMSEA} \leq 0.05)} < 0.001$; 90% CI (0.07, 0.07)). The reduced model depicted in Figure 1 presented satisfactory factor loadings and structural weights for all items and first-order factors, respectively.

Following these results, item 14 was reformulated with a different item wording, keeping the same content: 'I have been concerned about my physical integrity at school.' The 2024 sample was collected using a refined version of GSPS. A new CFA on the original model was conducted with the 2024 sample, and the fit to the data was satisfactory ($\chi^2_{(371)} = 4506.50$; $p < 0.001$; CFI = 0.97; TLI = 0.96; NFI = 0.96; SRMR = 0.06; RMSEA = 0.06;

TABLE 1 Demographic and professional characteristics of participants in samples 1 and 2.

Sample 2023				
	Female *n* = 1634	**Male** *n* = 285	**Non-binary** *n* = 46	**Overall** *N* = 1965
Age (years)				
M (SD)	50.4 (8.23)	50.3 (7.64)	47.2 (8.95)	50.3 (8.18)
Mdn [Min, Max]	50.0 [23.0, 69.0]	50.0 [24.0, 67.0]	47.0 [26.0, 65.0]	50.0 [23.0, 69.0]
Missing	8 (0.5%)	2 (0.7%)	1 (2.2%)	11 (0.6%)
Occupational group				
Teacher	1162 (71.1%)	224 (78.6%)	30 (65.2%)	1416 (72.1%)
Support staff	472 (28.9%)	61 (21.4%)	16 (34.8%)	549 (27.9%)
Professional experience at the current institution (years)				
M (SD)	9.74 (9.09)	10.4 (9.78)	8.57 (9.58)	9.81 (9.20)
Mdn [Min, Max]	6.00 [0, 42.0]	6.00 [1.00, 36.0]	4.00 [1.00, 40.0]	6.00 [0, 42.0]
Missing	3 (0.2%)	1 (0.4%)	0 (0%)	4 (0.2%)
Academic level				
Elementary education	87 (5.3%)	8 (2.8%)	1 (2.2%)	96 (4.9%)
Secondary education	248 (15.2%)	35 (12.3%)	14 (30.4%)	297 (15.1%)
Higher education	1262 (77.2%)	231 (81.1%)	28 (60.9%)	1521 (77.4%)
Missing	37 (2.3%)	11 (3.9%)	3 (6.5%)	51 (2.6%)
Sample 2024				
	Female *n* = 2449	**Male** *n* = 408	**Non-binary** *n* = 27	**Overall** *N* = 2884
Age (years)				
M (SD)	51.0 (8.60)	50.2 (8.93)	51.9 (8.17)	50.9 (8.65)
Mdn [Min, Max]	51.0 [20.0, 70.0]	50.0 [10.0, 69.0]	54.0 [34.0, 64.0]	51.0 [10.0, 70.0]
Missing	4 (0.2%)	1 (0.2%)	0 (0%)	5 (0.2%)
Occupational group				
Teacher	1660 (67.8%)	323 (79.2%)	17 (63.0%)	2000 (69.3%)
Support staff	789 (32.2%)	85 (20.8%)	10 (37.0%)	884 (30.7%)
Professional experience at the current institution (years)				
M (SD)	10.6 (10.0)	10.9 (10.6)	11.6 (9.22)	10.7 (10.1)
Mdn [Min, Max]	7.00 [0, 42.0]	6.00 [1.00, 42.0]	10.0 [1.00, 28.0]	7.00 [0, 42.0]
Missing	17 (0.7%)	1 (0.2%)	0 (0%)	18 (0.6%)
Academic level				
Elementary school	168 (6.9%)	20 (4.9%)	2 (7.4%)	190 (6.6%)
Secondary school	409 (16.7%)	38 (9.3%)	5 (18.5%)	452 (15.7%)
Higher education	1723 (70.4%)	329 (80.6%)	19 (70.4%)	2071 (71.8%)
Missing	149 (6.1%)	21 (5.1%)	1 (3.7%)	171 (5.9%)

TABLE 2 Items' distributional properties for Georgia School Personnel Survey.

Item	M	SD	Min	P_{25}	Mdn	P_{75}	Max	Histogram	SEM	CV	$Mode$	sk	ku
2023 Sample (n = 1,965)													
1	3.35	0.67	1	3	3	4	4		0.02	0.20	3	-0.78	0.50
2	3.67	0.53	1	3	4	4	4		0.01	0.14	4	-1.39	1.46
3	3.43	0.71	1	3	4	4	4		0.02	0.21	4	-1.23	1.52
4	3.52	0.65	1	3	4	4	4		0.01	0.18	4	-1.37	2.14
5	3.57	0.60	1	3	4	4	4		0.01	0.17	4	-1.33	1.92
6	3.39	0.66	1	3	3	4	4		0.01	0.19	4	-0.93	1.08
7	3.18	0.76	1	3	3	4	4		0.02	0.24	3	-0.75	0.40
8	3.12	0.73	1	3	3	4	4		0.02	0.23	3	-0.66	0.52
9	3.40	0.70	1	3	4	4	4		0.02	0.21	4	-1.06	0.93
10	3.44	0.72	1	3	4	4	4		0.02	0.21	4	-1.17	0.99
11	3.66	0.62	1	3	4	4	4		0.01	0.17	4	-1.88	3.30
12	3.51	0.62	1	3	4	4	4		0.01	0.18	4	-1.06	0.87
13	3.59	0.67	1	3	4	4	4		0.02	0.19	4	-1.70	2.78
14	2.90	1.17	1	2	3	4	4		0.03	0.40	4	-0.45	-1.36
15	3.04	0.84	1	3	3	4	4		0.02	0.27	3	-0.68	-0.02
16	3.67	0.60	1	3	4	4	4		0.01	0.16	4	-1.91	3.78
17	2.79	0.95	1	2	3	3	4		0.02	0.34	3	-0.47	-0.65
18	2.77	0.80	1	2	3	3	4		0.02	0.29	3	-0.47	-0.07
19	3.36	0.74	1	3	3	4	4		0.02	0.22	4	-1.07	0.94
20	3.46	0.70	1	3	4	4	4		0.02	0.20	4	-1.20	1.07
21	3.01	0.68	1	3	3	3	4		0.02	0.22	3	-0.44	0.50
22	3.01	0.61	1	3	3	3	4		0.01	0.20	3	-0.48	1.30
23	2.86	0.66	1	3	3	3	4		0.01	0.23	3	-0.56	0.82
24	3.02	0.69	1	3	3	3	4		0.02	0.23	3	-0.40	0.22
25	3.02	0.68	1	3	3	3	4		0.02	0.23	3	-0.43	0.37
26	2.85	0.70	1	2	3	3	4		0.02	0.24	3	-0.40	0.30
27	2.89	0.68	1	3	3	3	4		0.02	0.24	3	-0.45	0.52
28	2.70	0.81	1	2	3	3	4		0.02	0.30	3	-0.31	-0.34
29	2.80	0.76	1	2	3	3	4		0.02	0.27	3	-0.32	-0.11
2024 Sample (n = 2,884)													
Item	M	SD	Min	P_{25}	Mdn	P_{75}	Max	Histogram	SEM	CV	$Mode$	sk	ku
1	3.37	0.66	1	3	3	4	4		0.01	0.20	4	-0.87	0.82
2	3.71	0.51	1	3	4	4	4		0.01	0.14	4	-1.66	2.93
3	3.41	0.70	1	3	4	4	4		0.01	0.20	4	-1.19	1.61
4	3.56	0.60	1	3	4	4	4		0.01	0.17	4	-1.25	1.68
5	3.62	0.57	1	3	4	4	4		0.01	0.16	4	-1.39	1.99
6	3.45	0.63	1	3	4	4	4		0.01	0.18	4	-0.97	1.15
7	3.15	0.74	1	3	3	4	4		0.01	0.24	3	-0.72	0.52
8	3.19	0.68	1	3	3	4	4		0.01	0.21	3	-0.57	0.47
9	3.49	0.65	1	3	4	4	4		0.01	0.19	4	-1.11	0.98
10	3.46	0.70	1	3	4	4	4		0.01	0.20	4	-1.23	1.26
11	3.67	0.57	1	3	4	4	4		0.01	0.16	4	-1.78	3.17
12	3.56	0.59	1	3	4	4	4		0.01	0.16	4	-1.14	1.21
13	3.68	0.59	1	3	4	4	4		0.01	0.16	4	-2.01	4.49
14	2.91	1.20	1	2	3	4	4		0.02	0.41	4	-0.47	-1.40
15	3.19	0.79	1	3	3	4	4		0.01	0.25	3	-0.86	0.42
16	3.75	0.52	1	4	4	4	4		0.01	0.14	4	-2.28	5.83
17	3.04	0.87	1	3	3	4	4		0.02	0.29	3	-0.74	-0.02
18	2.93	0.79	1	3	3	3	4		0.01	0.27	3	-0.57	0.15
19	3.50	0.64	1	3	4	4	4		0.01	0.18	4	-1.15	1.17
20	3.61	0.59	1	3	4	4	4		0.01	0.16	4	-1.41	1.77
21	3.06	0.63	1	3	3	3	4		0.01	0.20	3	-0.39	0.79
22	3.06	0.56	1	3	3	3	4		0.01	0.18	3	-0.33	1.52
23	2.92	0.62	1	3	3	3	4		0.01	0.21	3	-0.60	1.37
24	3.10	0.67	1	3	3	4	4		0.01	0.22	3	-0.46	0.45
25	3.08	0.65	1	3	3	3	4		0.01	0.21	3	-0.43	0.61
26	2.94	0.66	1	3	3	3	4		0.01	0.23	3	-0.42	0.57
27	2.92	0.66	1	3	3	3	4		0.01	0.23	3	-0.49	0.74
28	2.72	0.78	1	2	3	3	4		0.01	0.29	3	-0.39	-0.14
29	2.80	0.74	1	2	3	3	4		0.01	0.26	3	-0.41	0.11

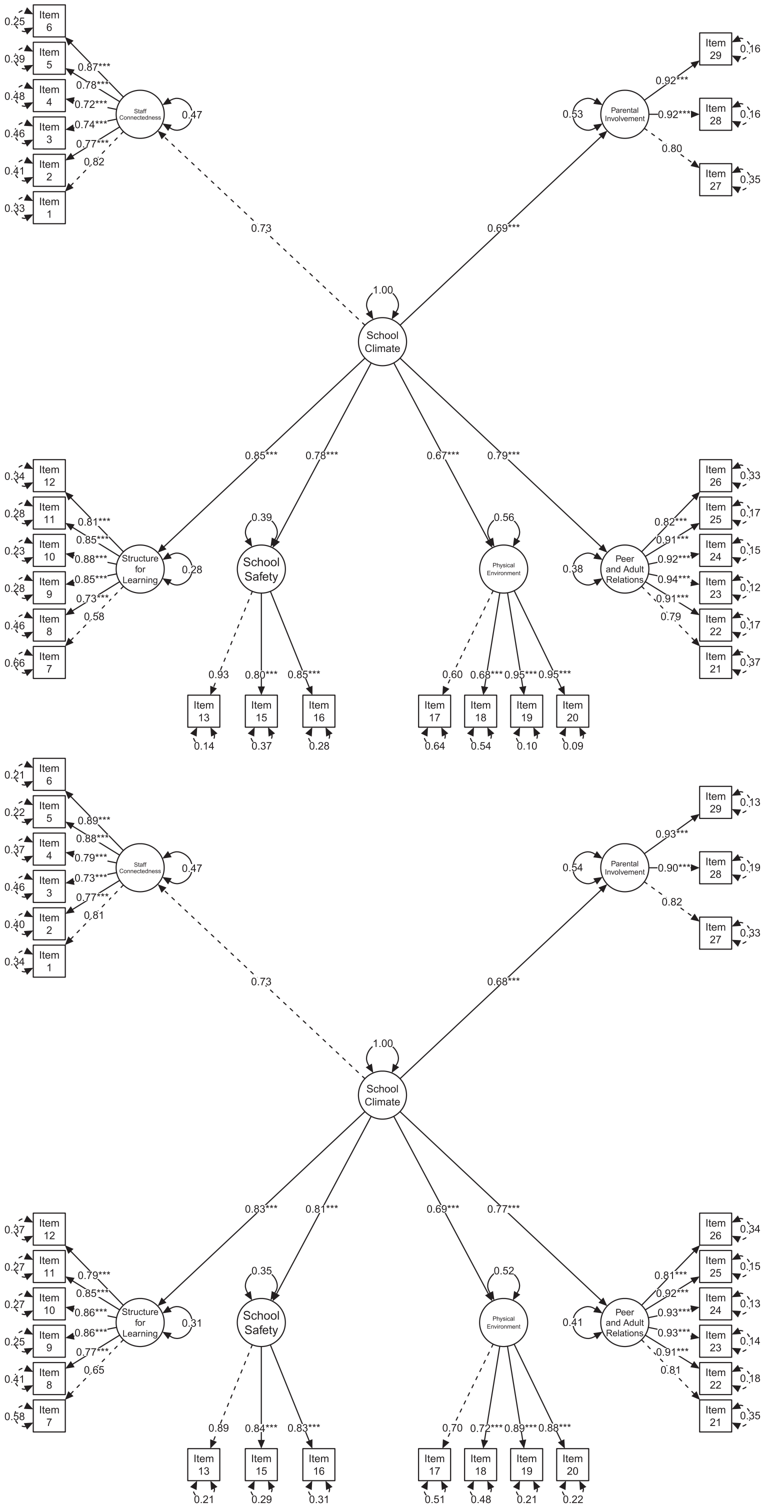

FIGURE 1 CFA diagram for 2023 sample (top) and 2024 sample (bottom). Standardised estimates. ***$p \leq 0.001$. Dotted lines indicate fixed parameters.

$p_{(\text{RMSEA}\leq 0.05)} < 0.001$; 90% CI (0.06, 0.06)). Once again, item 14 presented a problematic factor loading ($\hat{\lambda}_{Item\,14} = 0.148$). The item was removed and the modified model was tested. The reduced version presented a satisfactory fit to the data ($\chi^2_{(344)} = 3888.64$; $p < 0.001$; CFI = 0.97; TLI = 0.97; NFI = 0.97; SRMR = 0.05; RMSEA = 0.06; $p_{(\text{RMSEA}\leq 0.05)} < 0.001$; 90% CI (0.06, 0.06)). Figure 1 depicts the standardised results of the modified version of the GSPS using the 2024 sample.

In the 2023 and 2024 samples, item fit indices (infit and outfit) were generally consistent (Table 3). Most items showed satisfactory fit values (0.6–1.4), with some variations. Item 7 had high infit and outfit values, indicating potential misfit. Items 5, 6, 9, 11, 12, 13, 19, 20, 22, 23, 24, 25, 28, and 29 displayed low values, suggesting good fit. Items 3, 4, 17, 21, and 26 had higher values but remained within acceptable ranges. Overall, most items had fit indices close to 1, indicating a reasonable model fit across both samples.

TABLE 3 Items' infit and outfit mean square statistics.

	2023 sample		2024 sample	
Item	**Outfit**	**Infit**	**Outfit**	**Infit**
1	0.954	0.982	0.997	1.009
2	0.970	0.960	0.978	0.990
3	1.116	1.143	1.116	1.128
4	1.155	1.108	0.959	0.981
5	0.896	0.951	0.715	0.851
6	0.820	0.840	0.780	0.844
7	1.365	1.338	1.340	1.317
8	1.040	1.045	0.999	1.010
9	0.815	0.865	0.814	0.870
10	0.810	0.864	0.890	0.931
11	0.832	0.917	0.792	0.940
12	0.819	0.903	0.868	0.936
13	0.757	0.873	0.798	0.911
15	1.106	1.089	1.048	1.038
16	0.890	0.946	0.902	0.942
17	1.180	1.164	1.080	1.065
18	1.037	1.043	1.053	1.051
19	0.843	0.884	0.854	0.918
20	0.827	0.894	0.836	0.938
21	1.165	1.139	1.115	1.122
22	0.784	0.871	0.774	0.867
23	0.679	0.765	0.725	0.808
24	0.813	0.856	0.785	0.840
25	0.855	0.880	0.766	0.846
26	1.141	1.150	1.158	1.161
27	0.981	1.009	0.958	0.990
28	0.837	0.854	0.868	0.889
29	0.817	0.847	0.799	0.838

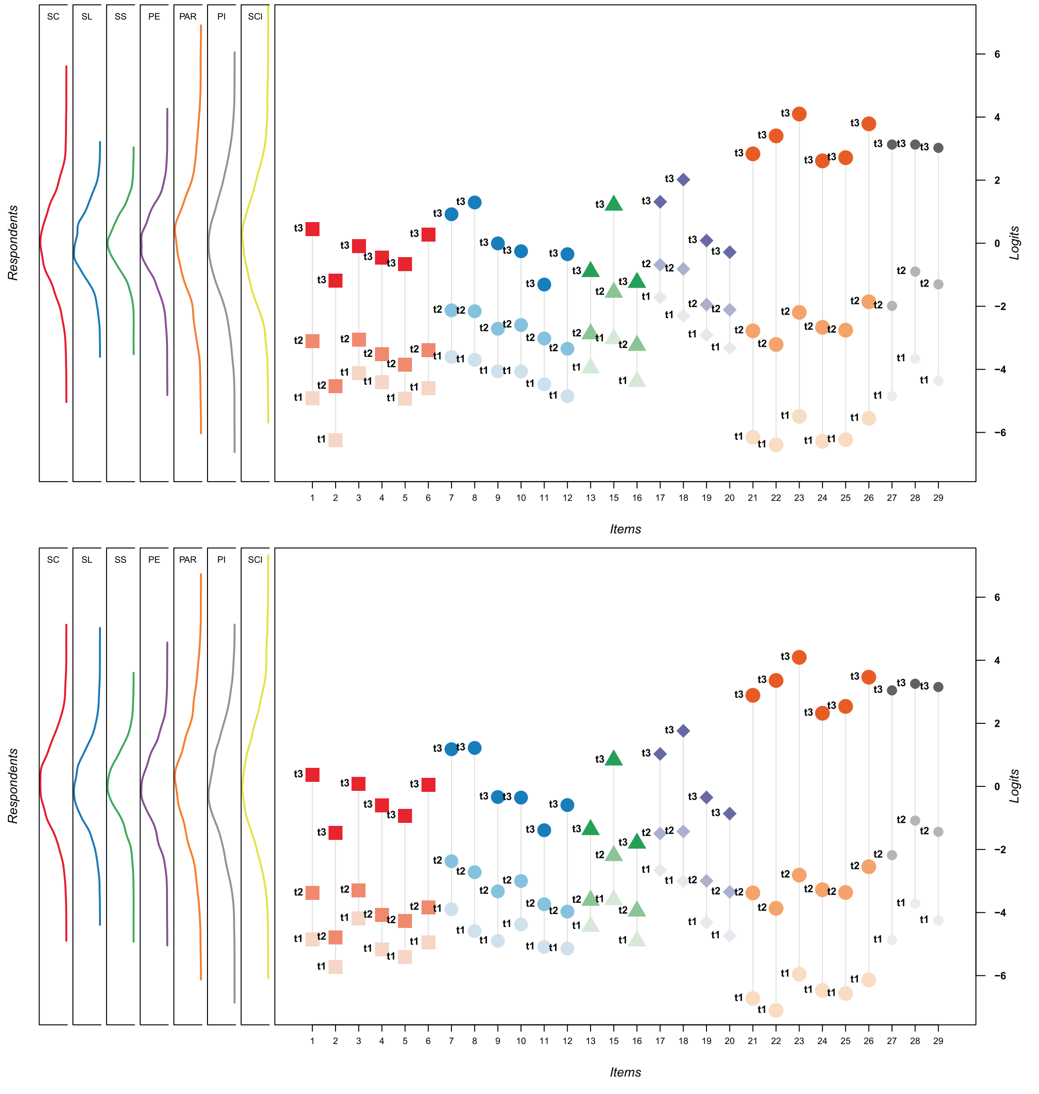

FIGURE 2 Wright map for 2023 sample (top) and 2024 sample (bottom). PAR, peer and adult relations; PE, physical environment; PI, parental involvement; SC, staff connectedness; SCI, school climate; SL, structure for learning; SS, school safety. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 2 presents a Wright map for the GSPS items in each sample, illustrating the relationship between participants' latent levels of school climate perceptions and their response probabilities. Both samples showed similar patterns. The dimensions of peer and adult relations and parental involvement had more dispersed thresholds, with the highest and lowest thresholds spread out. Other dimensions had more concentrated thresholds. All $\hat{\tau}_{2i}$ (threshold between the second and third answering options) were below 0 logits.

Reliability: Internal consistency

All first-order dimensions presented adequate estimates of reliability for both samples (Table 4). Regarding the second-order reliability estimates, both the 2023 sample ($\omega_{L1}=0.87$; $\omega_{\text{partial L1}}=0.97$; $\omega_{L2}=0.88$) and the 2024 sample ($\omega_{L1}=0.86$; $\omega_{\text{partial L1}}=0.97$; $\omega_{L2}=0.89$,

TABLE 4 Reliability estimates for Georgia School Personnel Survey.

Dimension	2023 sample				2024 sample			
	$\alpha_{ordinal}$	ω	AVE	EAP	$\alpha_{ordinal}$	ω	AVE	EAP
Staff connectedness	0.90	0.84	0.62	0.83	0.92	0.86	0.66	0.84
Structure for learning	0.89	0.85	0.62	0.87	0.90	0.86	0.64	0.87
School safety	0.86	0.82	0.74	0.80	0.87	0.80	0.73	0.81
Physical environment	0.78	0.81	0.66	0.78	0.83	0.80	0.64	0.78
Peer and adult relations	0.95	0.91	0.78	0.90	0.95	0.91	0.79	0.90
Parental involvement	0.90	0.86	0.78	0.84	0.90	0.86	0.78	0.84

EAP = 0.93) presented satisfactory evidence. The global score of school climate also presented good estimates of EAP ($EAP_{2023} = 0.93$; $EAP_{2024} = 0.93$).

Measurement invariance

For both samples, full uniqueness measurement invariance was achieved using the ΔCFI criterion ($\Delta CFI \leq -0.010$) for the GSPS across occupational groups (teachers and other occupations) and gender (female and male workers) (Table 5). Non-binary workers were not included in the multigroup CFA due to the small sample size ($n_{2023} = 46$; $n_{2024} = 27$).

Validity evidence based on relations with other variables

The measurement model tested to analyse the GSPS scores' convergent evidence with work engagement, burnout, job satisfaction and years of experience presented satisfactory fit to the 2023 data ($\chi^2_{(1408)} = 9424.96$; $p < 0.001$; CFI = 0.97; TLI = 0.96; NFI = 0.96; SRMR = 0.06; RMSEA = 0.05; $p_{(RMSEA \leq 0.05)} < 0.001$; 90% CI (0.05, 0.05)) and to the 2024 data ($\chi^2_{(1408)} = 11{,}930.05$; $p < 0.001$; CFI = 0.98; TLI = 0.98; NFI = 0.98; SRMR = 0.05; RMSEA = 0.05; $p_{(RMSEA \leq 0.05)} = 0.020$; 90% CI (0.05, 0.05)).

The reliability of the GSPS convergent measures was good for the 2023 sample (job satisfaction: $\omega = 0.83$; burnout: $\omega_{L1} = 0.84$; $\omega_{\text{partial } L1} = 0.96$; $\omega_{L2} = 0.88$; work engagement: $\omega_{L1} = 0.92$; $\omega_{\text{partial } L1} = 0.98$; $\omega_{L2} = 0.94$) and for the 2024 sample (job satisfaction: $\omega = 0.83$; burnout: $\omega_{L1} = 0.84$; $\omega_{\text{partial } L1} = 0.96$; $\omega_{L2} = 0.88$; work engagement: $\omega_{L1} = 0.93$; $\omega_{\text{partial } L1} = 0.98$; $\omega_{L2} = 0.95$).

The latent correlation pattern for the convergent measures was similar between both samples and satisfactory overall in terms of convergent evidence (Table 6). All convergent measures had statistically significant latent correlations with school climate. Job satisfaction and work engagement showed large positive correlations, while burnout had a large negative correlation. However, the correlation between school climate and years of experience at the current institution was small and negative.

DISCUSSION

A positive school climate has been associated with positive outcomes for students (Aldridge & McChesney, 2018; Erdem & Kaya, 2024; Hamlin, 2021; Van Eck et al., 2017) and teachers (Aldridge & Fraser, 2016; Collie et al., 2012; Gonzálvez et al., 2022; Grayson & Alvarez, 2008; Grazia & Molinari, 2021; Malinen & Savolainen, 2016; Saint et al., 2021; Zakariya, 2020).

TABLE 5 Measurement invariance for Georgia School Personnel Survey.

2023 sample					
Occupational groups ($n_{teachers}=1463$; $n_{other\ occupations}=549$)					
Model invariance	χ^2_{scaled}	**df**	$p_{\Delta\chi^2}$	**CFI$_{scaled}$**	**ΔCFI$_{scaled}$**
I—Configural	3651.605	688	–	0.963	–
II—Thresholds	3646.330	710	0.562	0.964	0.000
III—Factor loadings	3573.753	732	0.010	0.965	0.001
IV—Structural weights	3500.103	737	<0.001	0.966	0.001
V—Intercepts (first order)	3843.256	765	<0.001	0.962	−0.004
VI—Latent means	3871.491	771	<0.001	0.962	0.000
VII—Disturbances	4653.751	777	<0.001	0.952	−0.010
VIII—Residuals	4328.075	805	<0.001	0.956	0.004
Gender ($n_{females}=1634$; $n_{males}=285$)					
I—Configural	3440.241	688	–	0.967	–
II—Thresholds	3435.037	710	0.538	0.967	0.000
III—Factor loadings	3330.574	732	0.926	0.968	0.002
IV—Structural weights	3239.838	737	0.002	0.970	0.001
V—Intercepts (first order)	3224.837	765	0.078	0.970	0.001
VI—Latent means	3127.346	771	<0.001	0.971	0.001
VII—Disturbances	3236.372	777	<0.001	0.970	−0.001
VIII—Residuals	3563.131	805	<0.001	0.966	−0.004
2024 sample					
Occupational groups ($n_{teachers}=2000$; $n_{other\ occupations}=884$)					
Model invariance	χ^2_{scaled}	**df**	$p_{\Delta\chi^2}$	**CFI$_{scaled}$**	**ΔCFI$_{scaled}$**
I—Configural	4062.299	688	–	0.970	–
II—Thresholds	4079.379	710	0.303	0.971	0.000
III—Factor loadings	4060.826	732	<0.001	0.971	0.000
IV—Structural weights	3869.788	737	0.007	0.973	0.002
V—Intercepts (first order)	4095.502	765	<0.001	0.971	−0.002
VI—Latent means	4035.395	771	<0.001	0.971	0.001
VII—Disturbances	3967.967	777	<0.001	0.972	0.001
VIII—Residuals	4189.250	805	<0.001	0.970	−0.002
Gender ($n_{females}=2449$; $n_{males}=408$)					
I—Configural	3857.630	688	–	0.972	–
II—Thresholds	3841.455	710	0.696	0.972	0.000
III—Factor loadings	3776.335	732	0.017	0.973	0.001
IV—Structural weights	3582.748	737	0.059	0.975	0.002
V—Intercepts (first order)	3598.395	765	<0.001	0.975	0.000
VI—Latent means	3401.059	771	0.046	0.977	0.002
VII—Disturbances	4139.972	777	<0.001	0.970	−0.006
VIII—Residuals	3570.866	805	<0.001	0.976	0.005

Note: The χ^2_{scaled} column contains the robust test. The $\Delta\chi^2$ and $p_{\Delta\chi^2}$ columns contain the robust difference test which is a function of two standard (not robust) statistics.

TABLE 6 Correlations from the measurement model.

Variable	1	2	3	4	5
School climate (1)		0.51***	0.54***	−0.52***	−0.08**
Work engagement (2)	0.51***		0.86***	−0.78***	−0.09***
Job satisfaction (3)	0.55***	0.83***		−0.83***	−0.11***
Burnout (4)	−0.57***	−0.80***	−0.82***		0.09***
Years of experience at the current institution (5)	−0.06**	−0.07***	−0.07***	0.10***	

Note: ***p*≤0.01; ****p*≤0.001. Correlations above the diagonal are for the 2023 data, while correlations below the diagonal correspond to the 2024 data.

Assessing school climate with input from teachers and staff is essential, as their perspectives can provide important insights into the strengths and challenges of the school environment. This assessment helps identify areas where support may be needed and informs strategies to create a more cohesive and healthy school community, ultimately leading to better outcomes for both students and professionals. Several measures have been developed internationally, but there is a lack of instruments validated for the Portuguese population.

This study aimed to adapt the GSPS for European Portuguese and to provide validity evidence based on the internal structure and based on the relations to other variables. Hypothesis 1 posited that the GSPS would maintain its original dimensionality, consisting of one second-order factor with six first-order dimensions and 29 items. The results of the CFA partially supported this hypothesis. Item 14 was removed due to its low factor loading. The reduced model fit indices were within acceptable ranges, indicating that the proposed structure (with 28 items) adequately represents the data. This finding aligns with previous research on the GSPS (Saint et al., 2021), reaffirming the theoretical underpinnings of the survey (La Salle et al., 2018) and its utility in capturing a multidimensional construct of school climate, including dimensions related to academic climate, interpersonal relationships, emotional and physical safety, and institutional environment (Te Wang & Degol, 2016). The maintenance of the original dimensionality is critical for ensuring that the GSPS measures the intended constructs accurately and comprehensively. However, one item was dropped—item 14, which states 'I have been worried with my physical safety at school'—as it exhibited a low factor loading, even after different formulations of the item have been tested. One of the reasons that might contribute to this finding is the fact that this was the only reverse-coded item. Research has indicated that using reverse-coded items can worsen the fit of a model and often lead to the creation of separate, non-meaningful dimensions (Cassady & Finch, 2014; Clauss & Bardeen, 2020; Vigil-Colet et al., 2020).

Hypothesis 2 stated that the GSPS would exhibit satisfactory reliability. The findings supported this hypothesis, as all dimensions demonstrated high reliability, as measured by the four types of estimates used (α_{ordinal}, ω, AVE, and EAP). These results indicate that the items within each dimension homogeneously and consistently measure the same underlying construct. The values obtained in our study were similar to those obtained by Saint et al. (2021) in the US population, where alpha ranged from 0.79 to 0.94 for the subscale scores and 0.95 for the overall score of the GSPS. These findings support that globally, there is an applicable model of overall school climate with subdimensions representing the experiences of personnel in different aspects of school life.

Hypothesis 3 proposed that the GSPS would hold measurement invariance across occupational groups (teachers and other school staff members) and gender (female and male). Mirroring the findings obtained by Saint et al. (2021), our results indicated that the GSPS achieves full measurement invariance across both occupational groups and gender. This finding suggests that the GSPS assesses the construct uniformly across different subgroups within the school setting, supporting the use of the GSPS scores to perform comparisons across males and females and across teachers and other school staff. This psychometric property of the instrument is relevant, as different subgroups do not always have similar perceptions about school climate. For example, in a study by Capp et al. (2020b), teachers who taught students up to 4th grade had more positive school climate perceptions than teachers who taught older students, although no differences were found between teachers and pupil support staff (e.g., psychologists and therapists, among others). Thus, assessment instruments should allow fair comparisons across groups, so that informed and tailored interventions can be performed with the different subgroups of the school community.

Beyond the internal structure, the GSPS's validity evidence was further assessed by examining its scores in relation to other variables, namely job satisfaction, burnout, work engagement and tenure. As predicted in Hypothesis 4, the GSPS scores correlated positively with job satisfaction. This is a relationship that has been found frequently in research (Aldridge & Fraser, 2016; Grayson & Alvarez, 2008; Malinen & Savolainen, 2016; Otrębski, 2022; Thapa et al., 2013; Zakariya, 2020), as a school climate characterised by support, collaboration, safety and inclusivity leads to higher job satisfaction. The GSPS scores were also positively associated with work engagement. This finding is also consistent with previous research suggesting that a positive school climate boosts staff's work engagement by fostering a sense of belonging, professional confidence, work autonomy and involvement in decision-making processes (Klassen et al., 2010; Skaalvik & Skaalvik, 2014).

Also consistent with theoretical expectations was the finding that the GSPS scores correlated negatively with burnout. Several studies have suggested that negative school climate factors like disorder, lack of resources and poor leadership are linked to higher burnout among teachers (Alamos et al., 2022; Arens & Morin, 2016), while a positive, supportive climate can help prevent it (Fatou & Kubiszewski, 2018; Grayson & Alvarez, 2008). These findings have clear implications for practice, as the improvement of the school climate will likely have positive impacts on job satisfaction, engagement and burnout levels of the school staff. Regarding tenure time, although significant, the correlations were of negligible size. Studies on this relationship are scarce, but some previous research has suggested that teachers who experience more positive school climates are more likely to remain at their schools longer (Boyd et al., 2011). The findings of our study do not support this relationship. On the one hand, this result suggests that school climate is probably more related to other variables; on the other hand, this finding might be related to the way teachers and staff are hired and placed in Portuguese public schools. For example, some teachers hold permanent positions, while others have non-permanent or short-term contracts. Each year, schools announce vacancies and teachers are assigned to public schools through a centralised and highly competitive process managed by the Portuguese Ministry of Education. As a result, teacher mobility between schools is not usually an easy process and is more common among teachers with non-permanent positions, who often have limited control over where they will be placed. This is likely why our results do not indicate a meaningful relationship between tenure and school climate. Thus, a negative perception of school climate may be associated with higher levels of burnout, lower job satisfaction and reduced work engagement, but not necessarily a change of school.

Regarding limitations, although this study was conducted with two independent and large samples, the sampling method was non-probabilistic. Furthermore, it should be noted that most schools participated in both years of data collection, which raises the possibility that certain participants may have contributed to both samples. This overlap could affect the independence of the samples; thus, they were not merged for analysis. Information regarding the existence of actions to promote school climate in the participating schools was also not collected and should be addressed in future studies. Additionally, future studies should also include additional sources of validity evidence, such as evidence based on response processes or consequences of testing (American Educational Research Association, 2014).

While this study adapted a measure originally developed in the United States to the Portuguese educational context, with findings supporting the universal relevance of core GSPS dimensions, it also contributes to ongoing debates about the cultural specificity versus universal applicability of constructs such as school climate. Research has highlighted the importance of considering cultural and contextual factors when examining school climate (e.g., La Salle, 2018; Obeidat et al., 2024; Zhao & Jin, 2023), as country-specific educational policies, systems and practices and broader social, economic and political contexts can significantly influence it. However, evidence from previous cross-cultural studies based on students suggests certain dimensions of school climate (e.g., interpersonal relationships and safety) may be universally relevant, while others (e.g., parental involvement or structure for learning) might be expressed differently depending on cultural and educational context (La Salle, Rocha-Neves, et al., 2021). Similarly, a recent study using TALIS international datasets found varied patterns of cross-cultural differences in teachers' climate perceptions, underlining that what constitutes a positive school climate is not one-size-fits-all (Zhao & Jin, 2023). Future studies could benefit from cross-cultural comparisons of teachers' and school staff's perspectives to clarify which dimensions of school climate are experienced universally and which require culturally sensitive adaptations to accurately reflect local cultural and educational contexts. Investigating how dimensions of school climate influence various outcomes for school personnel (e.g., job satisfaction, work engagement, burnout) across different cultures would further clarify the universality and cultural specificity of the school climate construct.

CONCLUSION

The GSPS is designed to align with the understanding that school climate is a complex, multidimensional construct that reflects the overall quality of a school through the collective experiences and perceptions of its community members (Bear et al., 2017; Cohen et al., 2009; Mitchell et al., 2010; National School Climate Center, 2007; Thapa et al., 2013). It encompasses key dimensions related to academic environment, interpersonal relationships, safety and structure, which are central to the concept of school climate (Te Wang & Degol, 2016), thus providing a robust theoretical foundation. The GSPS is relatively concise, with three to six items per dimension, which reduces the burden on respondents and may lead to higher response rates. This study is the first to adapt the GSPS for the linguistic and cultural context of Portugal. CFA results supported a structure consistent with the theoretical dimensions of the measure. The study's findings demonstrate that, despite some dimensions having a limited number of items, the GSPS maintains high reliability. Additionally, convergent evidence was obtained through correlations with measures of job satisfaction, work engagement and burnout. These robust psychometric properties make the GSPS a tool with strong validity evidence for guiding school improvement efforts, educational policy decisions and research. Alongside the adaptation of student and family surveys for the Portuguese population, the GSPS will provide education professionals and researchers with a comprehensive system for assessing school climate, allowing for comparisons between student, teacher/staff and family perceptions.

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CONFLICT OF INTEREST STATEMENT
The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT
Data are available upon request from the authors.

ETHICS STATEMENT
This project received ethics approval from the Ethics Committee of Universidades Lusíada (JL/CE/CIPD/2303).

PATIENT CONSENT STATEMENT
All procedures involved in this study were carried out with full respect for the informed and explicit consent of the participants.

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