Personality and Individual Differences 248 (2026) 113484

Contents lists available at ScienceDirect

Personality and Individual Differences

journal homepage: www.elsevier.com/locate/paid

Demographic profile of Sensory Processing Sensitivity

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A R T I C L E I N F O

Keywords:
Sensory Processing Sensitivity
Demographic factors
Personality trait
Sensitivity levels
Well-being
Health
Descriptive study

A B S T R A C T

Sensory Processing Sensitivity (SPS) refers to a genetically-based temperament trait associated with enhanced awareness and response to environmental stimuli. SPS is the first framework to develop a psychometric tool that captures sensitivity to environments directly as a phenotypic trait in adults and children. Although there is abundant literature on SPS, no study so far has focused on demographic aspects. On a large sample from the general population and embedded in the perspective of different sensitivity levels previously identified in the literature (i.e., low, medium and high SPS), we explored, through latent class analysis, how SPS manifests at a demographic level. Our findings revealed that low-SPS, medium-SPS and high-SPS individuals can be characterised by probabilistic demographic profiles. The most likely profile of a highly sensitive participant in our sample included being a woman between 35 and 44 years old with university study level, married and with 2 children, employed at full time and owning or renting a house. Our study offers demographic evidence for the existence of three sensitivity levels and, for the first time, a demographic profile corresponding to the SPS personality trait is outlined. The findings may have practical implications in the context of clinical psychology, mental health interventions, and educational or workplace settings.

1. Introduction

1.1. Sensory Processing Sensitivity

Sensory Processing Sensitivity (SPS) refers to a personality trait found in around 20–35 % of the population (Aron & Aron, 1997; Pluess et al., 2018). It is characterised by greater depth of information processing, increased emotional reactivity and empathy, greater awareness of environmental subtleties, and ease of overstimulation (Aron et al., 2012; Greven et al., 2019).

Research in the last decade places SPS in the context of environmental sensitivity (ES), the ability found in most organisms to register, process, and respond to external factors (Pluess, 2015; Pluess & Boniwell, 2015). Some participants have been found to be much more sensitive than others to environmental influences (Lionetti et al., 2018). ES has been widely studied in relation to personality, genetics, and environment (Hicks et al., 2008; Murray et al., 2002; Willroth et al., 2023). From a theoretical perspective, ES includes three theories: i) Differential Susceptibility (Belsky, 1997; Belsky & Pluess, 2009); ii) Biological Sensitivity to Context (Boyce & Ellis, 2005) and iii) Sensory Processing Sensitivity (Aron & Aron, 1997). Although these all pose unique contributions to individual differences in interaction with the environment, they share the notion that sensitive individuals differ not only in their response to environmental adversity but also in response to positive/supportive aspects of the environment (Pluess, 2015). Unique to SPS is that it proposes an underlying phenotypic trait characterised by greater depth of information processing, increased emotional reactivity and empathy, greater awareness of environmental subtleties, and ease of overstimulation (Aron & Aron, 1997; Greven et al., 2019).

Previous theories (Aron et al., 2012; Boyce & Ellis, 2005) and empirical studies (see e.g., Wolf et al., 2008) have suggested the existence of different sensitivity groups. Some research based on high sensitivity measurement instruments (Highly Sensitive Child Scale, HSCS (Pluess et al., 2018 (Study 1)) and Highly Sensitive Person Scale,

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https://doi.org/10.1016/j.paid.2025.113484
Received 4 March 2025; Received in revised form 22 September 2025; Accepted 24 September 2025
Available online 7 October 2025
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HSPS (Aron & Aron, 1997)), through latent class analysis has specifically shown evidence supporting the existence of three sensitivity groups. In particular, a study conducted with a UK sample aged 8 to 19 years (Pluess et al., 2018 (Study 5)) suggested that there are 3 distinct groups with different levels of ES – low (approx. 25–35 %), medium (approx. 41–47 %), and high (20–35 %). Similarly, a study with a USA sample of undergraduate students also identified low (29 %), medium (40 %) and high (31 %) sensitivity levels (Lionetti et al., 2018).

1.2. Sociodemographic factors and Sensory Processing Sensitivity

Elevated SPS may enhance responsiveness to positive and supportive experiences (Boyce & Ellis, 2005), while concurrently increasing susceptibility to adverse clinical outcomes (Ahadi & Basharpoor, 2010; Bakker & Moulding, 2012). Recent research highlight sociodemographic factors' role in relation to personality and health (Løset & von Soest, 2023; Willroth et al., 2023). However, few studies have explored SPS from a demographic perspective. The main findings are summarised below.

1.2.1. Gender

Although some studies find no significant differences between SPS and gender (Chen et al., 2015), most show significant correlations (Andresen et al., 2018; Pieroni et al., 2024; Sperati et al., 2024), with women scoring higher (Panagiotidi et al., 2020; Şengül-İnal et al., 2018; Setti et al., 2022 (Study 1)). SPS factors show similar patterns: some studies report no differences (Schmitt, 2022 (Study 1)), while most find differences in some or all SPS factors (Chacón et al., 2021; Licht et al., 2020; Pérez-Chacón et al., 2023).

1.2.2. Age

Research on SPS and age shows inconsistent results. Some studies find no significant correlations (Schmitt, 2022 (Study 1); Setti et al., 2022 in 16–73-year-olds; Sperati et al., 2024 in 2.6–5.9-year-old preschoolers). Others report positive correlations: Costa-López et al. (2022) found significant increases in total score, EOE and AES comparing kindergarten and primary education groups (3–10 years), and Baryła-Matejczuk et al. (2022) found differences across three age groups (<15.5, 15.5–18, >18 years). Conversely, a negative correlation have been found between SPS and age for global scale (Panagiotidi et al., 2020), EOE (Schmitt, 2022 (Study 2)) and AES (Licht et al., 2020) though this last study reported positive correlation between LST and age.

1.2.3. Education level

Among the scarce research regarding SPS and educational level in adults, inconsistent results are also found, with positive (Pieroni et al., 2024), negative (Setti et al., 2022 (Study 1)) and no correlations (Setti et al., 2022 (Study 2)).

1.3. The present research

The cognitive and emotional characteristics of highly sensitive individuals could influence decisions such as studying, having children, or marrying, which may manifest demographically. An important issue is the manifestation of SPS throughout lifetime. The trait of high sensitivity is considered relatively stable (Aron & Aron, 1997). However, contemporary literature leans towards a more dynamic conception of personality traits (Bleidorn et al., 2021). Given the theoretical basis of SPS and contemporary literature, increases or decreases in SPS over time might be expected, depending on genetic or environmental factors.

The present research conducts a descriptive analysis of SPS in demographic terms, employing a retrospective ex post facto design and drawing on a large sample from the general adult Spanish population. Previous research shows evidence of a relationship between SPS and demographic variables; however, these relationships have not been completely clarified. The present study was approached from the perspective of different sensitivity groups (Lionetti et al., 2018) and through latent class analysis, the following research question was addressed: Can the different sensitivity groups (low-SPS, medium-SPS, high-SPS) be characterised by certain demographic profiles?. Demographic profiles of SPS would allow for the identification of the highly sensitive group, facilitating the implementation of targeted strategies to improve well-being.

2. Method

2.1. Participants

The initial sample consisted of 17,214 participants, of whom 7767 lived outside of Spain and 9447 were residents in Spain. In this study, only participants residing in Spain were considered. Thus, the initial sample consisted of 9447 participants with a minimum age of 18 years. Specifically, we recruited 3050 participants (32.29 %) aged 18 to 24 years, 2352 participants (24.9 %) aged 25 to 34 years, 2008 participants (21.26 %) aged 35 to 44 years, 1456 participants (15.41 %) aged 45 to 54 years, 478 participants (5.06 %) aged 55 to 64 years, 96 participants (1.02 %) aged 65 to 74 and 7 participants (0.07 %) older than 74 years and were 70.64 % women (N = 6673), 0.20 % transgender (trans) women (N = 19), 27.16 % men (N = 2566), 0.27 % trans men (N = 25), 1.13 % nonbinary (N = 107) and 0.60 % other gender (N = 57). For the purposes of data analysis: i) participants who specified their gender as women or trans women were considered women, participants who specified their gender as men or trans men were considered men; ii) nonbinary/others gender, age over 65 years, without education, and retirees were discarded due to low recruitment; iii) at the educational level, Master and PhD categories were grouped into a single category.

Moreover, to achieve better isolation of the intrinsic characteristics of each sensitivity level, participants with an HSPS score in the low-to-medium and medium-to-high sensitivity transitions were discarded for the latent class, resulting in a sample of 6507 participants.

2.2. Procedure

To ensure the necessary sample size, convenience sampling (by accessibility) was performed. Data were collected through an online questionnaire published on the website of the Spanish Association of High Sensitivity Professionals (https://pasespana.org/).

Participants signed an informed consent before beginning to answer the questionnaire. The complete questionnaire was about 20 min and included other measures not relevant to this study. The data was collected between the end of October 2021 and the middle of March 2022. Ethical approval for the study was granted by the Institutional Research Ethics Committee of the university where the research was conducted (CIPI/213006.45).

2.3. Measures

2.3.1. Demographic characteristics

The variables collected included gender, age range, marital status, number of children, studies completed, employment situation, type of working day and type of residence.

2.3.2. Sensory Processing Sensitivity

SPS was measured with HSPS-S (Chacón et al., 2021), a cross-cultural adaptation of the original Highly Sensitive Person Scale (Aron & Aron, 1997) to the adult Spanish population. HSPS-S is a 27-items scale with 5 factors or dimensions. All items were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). HSPS-S showed a good internal consistence with global Cronbach's α of 0.92.

2.4. Data analysis

2.4.1. Latent class analysis

To investigate whether different sensitivity groups exhibit specific demographic profiles (latent classes), we conducted latent class analysis (LCA) using the polytomous variable latent class analysis package in R (Linzer & Lewis, 2011). LCA identifies unobservable clusters within heterogeneous populations based on categorical response patterns (Lazarsfeld & Henry, 1968; McCutcheon, 1987) with recent applications in child mental health (Petersen et al., 2019), adolescent behavior (Fine et al., 2023), substance use patterns (Schmidt et al., 2022), and social disadvantage research (Jones et al., 2024).

This technique segments individuals by scoring patterns rather than outcome associations, identifying classes with unique characteristics where members are relatively similar. We conducted LCA on our polytomous variables (demographic and SPS level). We specified three sensitivity levels based on literature percentile criteria: 30 % low-SPS, 40 % medium-SPS, and 30 % high-SPS (Lionetti et al., 2018; Pluess et al., 2018). We tested five unconditional models (one to five clusters) using an algorithm producing 20 models per class with up to 3000 iterations. Model evaluation used Bayesian information criterion (BIC), adjusted BIC, adjusted Akaike information criteria (AIC), and Lo-Mendell-Rubin tests. Entropy values indicated classification accuracy, emphasizing within-class similarities and between-class differences regarding sensitivity levels.

3. Results

3.1. Descriptive statistics of demographic variables

According to Lionetti et al. (2018), the participants were classified within 3 sensitivity levels using a percentile criterion. The cut-off scores established in our sample were 5.11 (low-SPS to medium-SPS), and 6.07 (medium-SPS to high-SPS). Each sensitivity level included only participants whose HSPS score fell within the mean ± standard deviation of HSPS for that sensitivity level. The mean HSPS-S scores and standard deviations of all variables segregated into the three SPS levels are shown in Table 1.

3.2. Demographic profiles related to SPS

The three latent classes model demonstrated acceptable goodness-of-fit indices and excellent entropy in the data analysis (Table 2). This statistical outcome, contextualised within the prior theoretical framework, establishes Model 3 as the most parsimonious, interpretable, and scientifically consistent solution. For detailed justification see Appendix A (Supplementary material). This model included 6507 observations, 80 estimated parameters and 6427 degrees of freedom and obtained a reasonable adjustment index and an adequate entropy level close to 1, which explained 85 % of the frequency variability in the categories of the variables of interest.

The conditional probabilities of each category for the variables of interest in the three classes are displayed in Fig. 1 and Table S1 (Appendix B, Supplementary material). The LCA generated three probabilistic profiles attending to the level of sensitivity (low-SPS, medium-SPS, high-SPS). Based on the conditional probabilities of co-occurrence of the

Table 1
Descriptive statistics of the variables segregated into the three SPS levels.

Descriptive information		HSPS-S		
		Low (35,6 %)	Medium (33,8 %)	High (30,6 %)
Gender	Male (28,8 %)	4.16 (0.65) [58.8 %, 47.5 %]	5.63 (0.16) [27.9 %, 23.8 %]	6.50 (0.18) [13.3 %, 12.6 %]
	Female (71.2 %)	4.31 (0.58) [26.3 %, 52.5 %]	5.65 (0.16) [36.2 %, 76.2 %]	6.52 (0.19) [37.6 %, 87.4 %]
Age (years)	18–24 (32.6 %)	4.27 (0.59) [53.1 %, 48.5 %]	5.62 (0.16) [33.6 %, 32.4 %]	6.46 (0.18) [13.3 %, 14.1 %]
	25–34 (25.2 %)	4.22 (0.65) [36.0 %, 25.4 %]	5.65 (0.16) [36.3 %, 27.0 %]	6.50 (0.18) [27.7 %, 22.8 %]
	35–44 (22.0 %)	4.20 (0.62) [26.9 %, 16.6 %]	5.65 (0.16) [32.7 %, 21.3 %]	6.53 (0.18) [40.4 %, 29.1 %]
	45–54 (15.7 %)	4.20 (0.71) [16.3 %, 7.2 %]	5.68 (0.15) [31.1 %, 14.4 %]	6.55 (0.19) [52.6 %, 27.0 %]
	55–64 (4.6 %)	4.28 (0.56) [17.7 %, 2.3 %]	5.68 (0.16) [35.7 %, 4.9 %]	6.54 (0.19) [46.6 %, 7.0 %]
Civil status	Single (50.4 %)	4.25 (0.62) [45.1 %, 63.8 %]	5.63 (0.16) [34.2 %, 51.1 %]	6.50 (0.19) [20.7 %, 34.1 %]
	Lives as a couple (17.0 %)	4.29 (0.59) [24.5 %, 11.7 %]	5.65 (0.16) [36.9 %, 18.5 %]	6.50 (0.17) [38.6 %, 21.4 %]
	Married (20.1 %)	4.18 (0.64) [25.7 %, 4.5 %]	5.66 (0.16) [31.5 %, 18.7 %]	6.55 (0.19) [42.8 %, 28.1 %]
	Separated (2.6 %)	4.14 (0.68) [31.0 %, 2.3 %]	5.67 (0.16) [33.3 %, 2.6 %]	6.53 (0.19) [35.7 %, 3.1 %]
	Divorced (5.5 %)	4.20 (0.70) [23.0 %, 3.6 %]	5.66 (0.15) [26.9 %, 4.4 %]	6.52 (0.20) [50.1 %, 9.0 %]
	Widowed (0.6 %)	4.24 (0.44) [27.8 %, 0.4 %]	5.64 (0.11) [30.5 %, 0.5 %]	6.50 (0.17) [41.7 %, 0.8 %]
	Other (3.8 %)	4.37 (0.55) [34.5 %, 3.7 %]	5.64 (0.16) [37.4 %, 4.2 %]	6.50 (0.16) [28.1 %, 3.5 %]
Number of children	No children (68.2 %)	4.27 (0.59) [38.3 %, 73.3 %]	5.64 (0.16) [35.3 %, 71.2 %]	6.50 (0.19) [26.4 %, 59.0 %]
	1 child (13.5 %)	4.21 (0.65) [31.1 %, 11.7 %]	5.67 (0.16) [30.4 %, 12.1 %]	6.53 (0.18) [38.5 %, 16.9 %]
	2 children (14.0 %)	4.15 (0.69) [27.0 %, 10.6 %]	5.67 (0.16) [30.9 %, 12.8 %]	6.55 (0.19) [42.1 %, 19.3 %]
	3 or more children (4.3 %)	3.98 (0.68) [36.0 %, 4.4 %]	5.65 (0.17) [30.2 %, 3.9 %]	6.54 (0.19) [33.8 %, 4.8 %]
Educational level	Primary (12.3 %)	4.25 (0.59) [43.1 %, 14.8 %]	5.63 (0.16) [33.5 %, 12.1 %]	6.53 (0.20) [23.4 %, 9.4 %]
	Secondary (27.8 %)	4.25 (0.63) [47.3 %, 37.0 %]	5.64 (0.16) [32.3 %, 26.6 %]	6.50 (0.19) [20.4 %, 18.5 %]
	Professional training (18.0 %)	4.26 (0.60) [29.3 %, 14.9 %]	5.65 (0.16) [33.1 %, 17.7 %]	6.52 (0.19) [37.6 %, 22.3 %]
	University degree (27.1 %)	4.20 (0.64) [31.4 %, 23.9 %]	5.65 (0.16) [33.7 %, 27.0 %]	6.52 (0.19) [34.9 %, 30.9 %]
	Master or PhD (14.8 %)	4.25 (0.58) [22.8 %, 9.4 %]	5.66 (0.16) [38.0 %, 16.6 %]	6.52 (0.18) [39.2 %, 18.9 %]
Employment	Unemployed (33.5 %)	4.26 (0.59) [43.3 %, 40.8 %]	5.63 (0.17) [32.7 %, 32.5 %]	6.52 (0.19) [24.0 %, 26.3 %]
	Employed (66.5 %)	4.23 (0.63) [31.7 %, 59.2 %]	5.65 (0.16) [34.3 %, 67.5 %]	6.52 (0.19) [34.0 %, 73.7 %]
Work dedication	Not working (32.8 %)	4.26 (0.59) [42.1 %, 38.8 %]	5.63 (0.17) [33.5 %, 32.6 %]	6.52 (0.18) [24.4 %, 26.1 %]
	Partial term (14.1 %)	4.30 (0.56) [34.6 %, 13.7 %]	5.65 (0.16) [32.7 %, 13.7 %]	6.52 (0.19) [32.7 %, 15.1 %]
	Complete term (45.7 %)	4.19 (0.67) [31.3 %, 40.0 %]	5.66 (0.15) [34.2 %, 46.2 %]	6.52 (0.19) [34.5 %, 51.6 %]
	Other term (7.4 %)	4.23 (0.56) [35.9 %, 7.5 %]	5.64 (0.16) [34.4 %, 7.5 %]	6.52 (0.17) [29.7 %, 7.2 %]
Residence	Parents/tutors (39.6 %)	4.26 (0.60) [50.3 %, 55.9 %]	5.62 (0.16) [33.2 %, 38.9 %]	6.49 (0.19) [16,5 %, 21.4 %]
	Share house (11.4 %)	4.24 (0.63) [37.6 %, 12.0 %]	6.65 (0.15) [34.2 %, 11.6 %]	6.51 (0.18) [28.2 %, 10.5 %]
	Rent/own house (49.0 %)	4.21 (0.65) [23.3 %, 32.1 %]	5.66 (0.16) [34.2 %, 49.5 %]	6.53 (0.19) [42.5 %, 68.1 %]

Note. i) Column 2: demographic variable category (frequency of the category in the total sample, N = 6507) ii) Columns 3–5: normalised mean HSPS-S score(SD) [% of participants in the row category who are in the column's sensitivity level, % of participants in the column's sensitivity level who are in the row's sociodemographic variable category].

categories in the demographic variables, analysis showed that the highest probability (38.02 %) of class membership in our sample was for the cluster accounting for a medium sensitivity profile. Low-SPS achieved 32.21 % of conditional probability and high-SPS attained 29.77 %, which is in line with the distribution of high sensitivity people in the general population. The most likely profile of a highly sensitive participant in our sample included being a woman (75 %) between 35 and 44 years old (39 %) with university study level (34 %), married (54 %) and with 2 children (39 %), employed (79 %) at full time (61 %) and owning or renting a house (87 %). The most likely profile of a participant with medium sensitivity included being a woman (73 %) between 25 and 34 years old (53 %) with university study level (40 %), single (64 %) and without children (92 %), employed (97 %) at full time (72 %) and owning or renting a house (57 %). Finally, the most likely profile of a participant with low sensitivity included being a woman (66 %) between 18 and 24 years old (81 %) with secondary study level (52 %), single (82 %) and without children (96 %), unemployed (70 %) and living with parents or tutors (83 %).

4. Discussion

4.1. Demographic profiles related to SPS

The existence of different sensitivity groups has been previously suggested by several theories (Aron et al., 2012; Boyce & Ellis, 2005) and empirical studies (see e.g., Wolf et al., 2008). More specifically, regarding Sensory Processing Sensitivity, Pluess et al. (2018 (Study 1)) suggested that there are 3 distinct groups of sensitivity based on a sample with 3581 participants aged 8 to 19 years. In line with this, Lionetti et al. (2018) suggested the existence of 3 levels of sensitivity based on a sample that included 906 psychology undergraduates.

Embedded in this context, the present research makes mainly three general contributions. First, the three-class latent model reinforces evidence supporting the three-level sensitivity perspective, using a large sample from the general population (ages 18–64) and a broader demographic spectrum than previous studies. Second, new in our study is the finding that these sensitivity levels can be characterised by probabilistic demographic profiles and for the first time, a demographic profile corresponding to the SPS personality trait (high sensitivity) is outlined. Third, based on a large sample, our study highlights and discusses the significance of demographic factors in general, and age and gender in particular, within the context of SPS. Significant theoretical and practical implications are examined throughout the discussion.

Consistently, both the descriptive statistics and the results derived from the latent class analysis conducted in our study revealed that the demographic characteristics of the population can provide information regarding the SPS level. When the most likely demographic profiles found for the different sensitivity levels are put together, age emerges as a demographic variable with a notable impact on sensitivity levels. Moreover, age was the only variable in our LCA model for which the maximum conditional category response probability across different classes (sensitivity levels) corresponded to different age ranges, that is, different categories of this demographic variable. More specifically, our results suggest that there may be a shift in sensitivity levels consistent with age-related variations, where younger individuals tend to exhibit lower sensitivity, which is especially noticeable in the early stages of adulthood (Figs. S1–S3, Appendix C, Supplementary material). This result is consistent with a previous study conducted with a Spanish sample aged 6 to 10 years (Costa-López et al., 2022), which reported an increase in SPS levels with age. Other recent study conducted with a sample of Polish adolescents and young adults (aged 12–25) (Baryła-Matejczuk et al., 2022) found similar results when analysing SPS by age groups. Thus, our findings regarding age and SPS level could be explained, at least partially, by changes occurring during development. However, it is important to note that, in strict terms, developmental processes cannot be inferred from a cross-sectional study.

In relation to the gender variable, in the aforementioned study (Baryła-Matejczuk et al., 2022), differences between age groups (<15.5, 15.5–18, >18 years) were found for both male and female. In our study, from a gender perspective, a remarkable finding emerged when the sample was divided by sensitivity levels. Specifically, although our sample was predominantly female (approximately 70 %), the proportion of men and women was similar in the low-sensitivity group, whereas women accounted for 76 % of participants in the medium-sensitivity group, rising to 87 % in the high-sensitivity group. This revealed marked gender differences in relation to sensitivity levels and a potential SPS-gender-age interaction. Ueno et al. (2019) reported age-related SPS differences that did not vary by sex. Our study corroborates that SPS varies with age for both genders. Moreover, it reveals unique lifespan patterns in HSPS scores for men and women (Fig. S3, Appendix C, Supplementary material). Many different factors could be contributing to this result. These may include lifestyle differences and cultural stereotypes regarding sensitivity and gender (Aron & Aron, 1997), interaction with the environment (Assary et al., 2021) and biological differences in sensory threshold (Kim et al., 2004), including potential genetic-age-gender interactions (Leong et al., 2010).

On the other hand, it is reasonable to expect that the differences identified in gender and age across the different sensitivity levels would also manifest in other demographic factors, including the number of children, marital status, type of residence, or even educational level. However, contributions beyond gender and age to the demographic manifestation of SPS should not be dismissed. In this regard, existing empirical evidence supports the demographic manifestation found for this personality trait. Fundamentally, gender and age, but also educational level, culture and professional sector, have been found to correlate with SPS (Andresen et al., 2018; Aron et al., 2010; Chacón et al., 2021). In this regard, cultural differences in the perception of sensitivity, the acceptance of emotional expressiveness, and exposure to environmental stimuli may shape the manifestation of the trait (Aron et al., 2010). Similarly, career choices could be influenced by SPS levels, as high-SPS individuals might gravitate towards occupations that favour autonomous work or creativity, while those with low SPS might prefer more structured and dynamic work environments (Andresen et al., 2018). In addition, characteristic cognitive-emotional processing in highly sensitive persons could account for their twofold greater divorce/separation probability versus less sensitive groups (Table 1). Thus, SPS may manifest demographically, contributing to the probabilistic profiles identified.

Table 2
Values of the fit indicators for model comparisons in latent class analysis.

	LL	Rdf	BIC	aBIC	cAIC	LLR	Entropy
Model 1	−64,080.66	6481.00	128,389.60	128,307.00	128,415.60	33,505.04	
Model 2	−57,456.94	6454.00	115,379.20	115,210.80	115,432.20	20,257.60	0.88
Model 3	**−55,932.72**	**6427.00**	**112,567.90**	**112,313.70**	**112,647.90**	**17,209.17**	**0.85**
Model 4	−54,960.56	6400.00	110,860.7	110,520.6	110,967.7	15,264.85	0.87
Model 5	−54,389.37	6373.00	109,955.4	109,529.5	110,089.4	14,122.47	0.84

Note: LL Loglikelihood, Rdf Residual degree of freedom, BIC Bayesian information criterion, aBIC Adjusted Bayesian information criterion, aAIC Adjusted Aikakes' information criteria; LLR Likelihood ratio: Lo-Mendell-Rubin adjusted likelihood ratio tests. The selected model is highlighted in bold (see Appendix A in the Supplementary Material for further details regarding model selection).

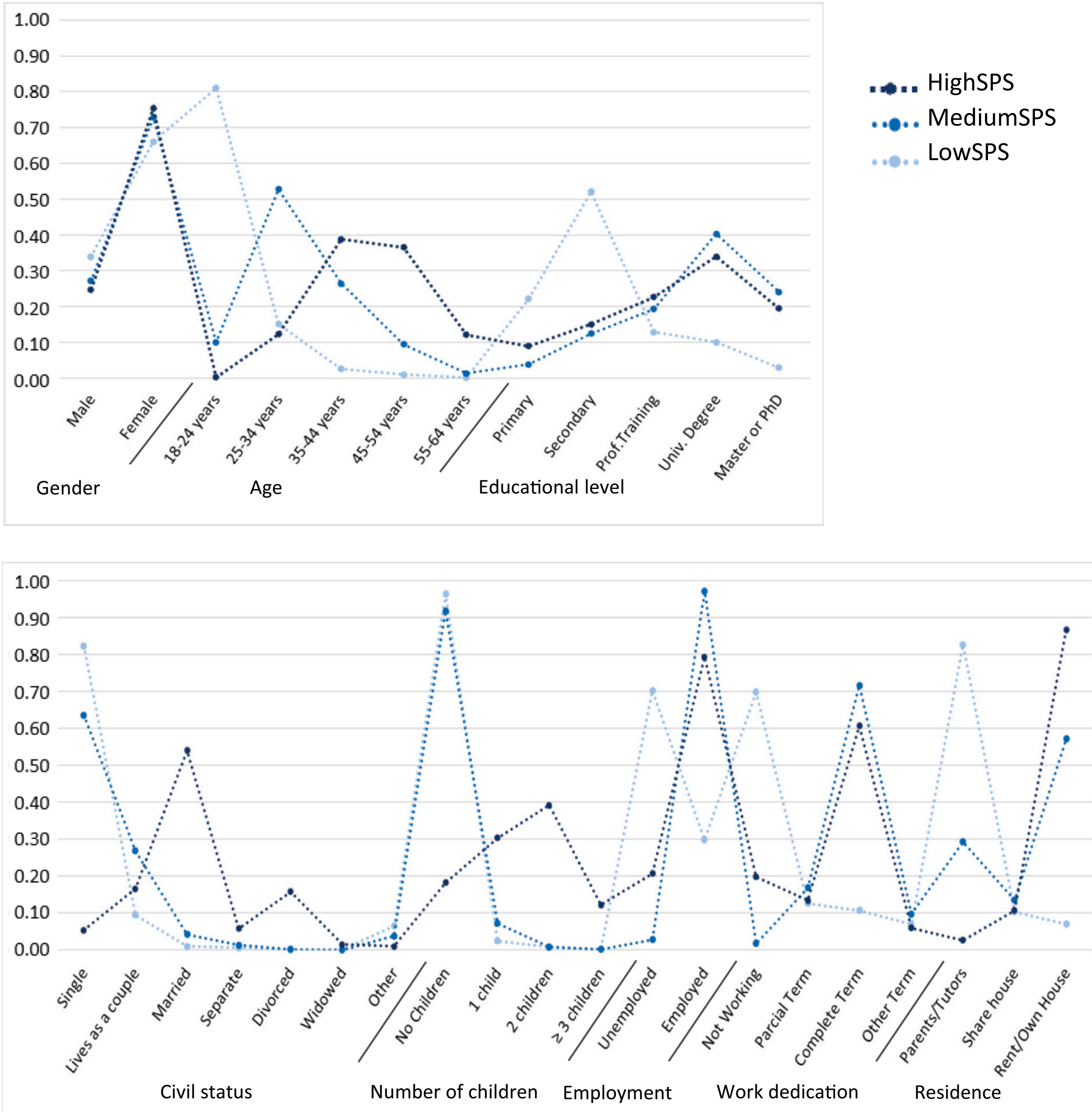

Fig. 1. Conditional plot for the three latent classed model. Probability of 32.21 for low-SPS (class 1), 38.02 for medium-SPS (class 2), and 29.77 for high-SPS (class 3). The data points are connected to enhance the visualisation of class-specific patterns.

4.2. Identification of sensitivity groups: LCA-based cut-offs vs percentile-tertile criteria

The identification of sensitivity groups remains partially unresolved in SPS research. Cut-off scores are crucial in studies with small samples or applied contexts for estimating individual sensitivity levels.

Previous studies have employed LCA, a data-driven and hypothesis-free approach (Pluess et al., 2018), to explore sensitivity groups using the HSP/HSC instruments. Specifically, Lionetti et al. (2018) conducted LCA on an adult sample (mean age = 19.2 years; 62.3 % female; N = 906 American psychology undergraduates), identifying a distribution of approximately 30 %-low, 40 %-medium, and 30 %-high sensitivity. Similarly, Pluess et al. (2018) applied LCA on samples comprising children and adolescents (aged 11–19 years), and identified three distinct sensitivity groups: low (approx. 25–35 %), medium (approx. 41–47 %), and high (approx. 20–35 %). Both studies aimed to determine the optimal number of sensitivity classes and explore their distribution and overlap, proposing preliminary cut-off scores. As Pluess et al. (2018) noted, given that HSC scores vary across cultures—a matter still under investigation—the proposed cut-off scores should be considered indicative rather than definitive. It may be more appropriate to apply a 30/40/30 percentile-based criterion within each sample to identify sensitivity groups.

Accordingly, we employed the 30/40/30 percentile criterion to identify sensitivity groups (low/medium/high-SPS), as it represents the most conservative approach and suits our study design. Nevertheless, given the sample size and demographic diversity, our dataset provides a suitable experimental condition to further explore and refine methods for identifying sensitivity groups. Specifically, we compared cut-off scores derived from a LCA conducted on all HSPS-S items with those obtained by directly applying percentile/tercile-based criteria (Table 3).

Using LCA-derived cut-off scores, 40 % of our sample were classified as highly sensitive, a proportion notably higher than the 30 % obtained through the direct application of the 30/40/30 percentile criterion. In heterogeneous samples, LCA-derived cut-off scores may introduce uncertainty due to the distribution of data across latent classes, whereas they may be appropriate in more homogeneous samples such as the one used by Lionetti et al. (2018). It is important to note that their sample consisted of undergraduate students, whose response variability was considerably lower than in our study. The greater dispersion in our data may lead to even more overlap than observed by Lionetti et al. (2018), due to the inherent heterogeneity of our sample.

Based on our findings and previous studies, the percentile-based criterion appears to be a statistically conservative and appropriate method for identifying sensitivity groups in sufficiently large general samples. Being conservative to ensure that the percentile-based criterion (30/40/30) yields stable estimates, we recommend minimum sample sizes of 200–300. For smaller samples, the increased error leads to wider confidence intervals, which are less useful for isolating subgroups. In such cases, it may be more appropriate to use cut-off scores derived from larger normative populations with similar demographic characteristics.

4.3. Strengths and limitations

The present study is the first to examine the demographic characteristics related to SPS. Additionally, we explored these characteristics with the precision conferred by the adoption of a sensitivity levels perspective and conducted the study on a large sample from the general population. Another important strength is that the high sample size allowed us to discard the participants with HSPS scores located in the transitions between sensitivity levels, which leads to greater robustness of the results, due to better isolation of the demographic characteristics of each sensitivity level.

However, the study has some limitations. First, it should be noted that the three latent classes in the model do not precisely match the three sensitivity levels, rather each class is accounting more likely than the others for one sensitivity level. Second, the high proportion of female gender in our study could limit the generalization of the results to the general population and additional study will be necessary to clarify this issue. However, this limitation is minimised by the evidence provided in our study and previous studies about the higher SPS level and greater proportion of high-SPS in women. Third, when interpreting the results, it should take into account that this is a cross-sectional study, not longitudinal, with inherent limitations. Finally, considering critical thinking, possible non-trait-based explanations (including socio-economic factors, geography or family environment) might also influence the observed phenomenon.

4.4. Implications and future research

Our study reveals that ES, at least as captured by the HSPS instrument (Greven et al., 2019), varies both over the lifespan and between individuals, increasing between ages 18 and 54 before a potential decline. This represents a key theoretical contribution, given the scarcity of longitudinal research on ES, SPS, and high-SPS. Although not longitudinal, our large sample size enables "developmental and environmental" comparisons across age groups.

Using HSPS and standard percentile-based sensitivity group criteria, our study reveals elevated rates of high-SPS, particularly among women in specific age ranges. This does not undermine the validity of our findings, as age- and gender-related variations in SPS are well-supported. However, there is scope for optimising sensitivity group classification. Future research should elucidate the nature of these findings to adopt more appropriate criteria for identifying sensitivity groups, taking demographic characteristics into more precise account.

The identified demographic profiles could help reduce negative clinical outcomes commonly observed in high-SPS individuals while enhancing their more advantageous traits, by promoting personalised interventions (e.g., in clinical psychology, workplace environments, or educational settings) and increasing SPS visibility among the population (Morales-Botello et al., 2026). Future research should explore SPS demographics across cultures, alongside the potential influence of parenthood particularly in women. Incorporating an alloparenting perspective (Kenkel et al., 2017) could also offer valuable insights in the context of SPS.

In summary, our findings highlight the importance of considering demographic factors when studying SPS and suggest the need for further research to explore more thoroughly how these factors interact with SPS in different contexts.

Table 3
Cut-off scores for low, medium and high SPS obtained with LCA vs percentiles/tertiles criteria.

Classification method	Low	Medium	High
LCA (scale 1–7)	≤4.94	4.95–5.31	>5.31
Percentiles (30–70)	≤5.11	5.12–6.07	>6.07
Tertiles (33–67)	≤5.22	5.23–6.00	>6.00

Note: LCA, Latent class analysis. Descriptive statistics of the sample: Total N: 9447; Overall Mean (scale 1–7): 5.49; Standard Deviation: 0.9; Range: 1–7.

5. Conclusion

The present study is the first to focus on demographic aspects associated with SPS. Based on a large sample from the general population, this work revealed the most probable demographic profiles associated with each sensitivity level (low-SPS, medium-SPS and high-SPS). Consequently, a demographic profile of the highly sensitive person was portrayed. These findings may substantially impact in the context of clinical psychology, workplace environments, and educational settings, facilitating the identification of target populations for the application of therapies, strategies, or policies that promote physical and emotional well-being.

CRediT authorship contribution statement

María Luz Morales-Botello: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Moisés Betancort:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Manuela Pérez-Chacón:** Writing – review & editing, Investigation. **Rosa-María Rodríguez-Jiménez:** Writing – review & editing, Investigation. **Antonio Chacón:** Writing – review & editing, Investigation.

Ethical statement

Ethical approval for the study was granted by the Institutional Research Ethics Committee of the Universidad Europea de Madrid (Ref: CIPI/213006.45).

Declaration of competing interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Acknowledgements

This work was partially supported by a grant from the Universidad

Europea de Madrid ("Study of the High Sensitivity trait and its relationship with psychological and contextual variables in adults and young adults in Spain"; Ref: 2022/UEM10; PI: Mª Luz Morales Botello).

Appendix. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.paid.2025.113484.

Data availability

Data will be made available on request.

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