Lifespan Variation in Perceptual Style Along an Autism–Schizotypy Continuum Explains Individual Responses to External Uncertainty

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ABSTRACT

Individuals differ in how they weigh prior knowledge against sensory evidence. This cognitive–perceptual style has been proposed to vary along a continuum from autism–spectrum-like (ASD) to schizophrenia–spectrum-like (SSD) processing. In the present study, we first introduce a refined method for estimating individuals' positions on this continuum by re-combining subscales of established autism and schizotypy questionnaires with a newly validated five-factor model for the autism questionnaire (AQ). Second, using a large, age-diverse adult sample (N = 340, age 18–82), we show that cognitive-perceptual style shifts systematically across the lifespan, with older adults exhibiting more sensory-driven, ASD-like profiles. Third, a total of over 160,000 self-paced reading times reveal that individuals with more sensory-driven styles show heightened sensitivity to lexical predictability, particularly in older age. Fourth, individuals' intrinsic response dynamics, indexed by autocorrelations of reading times, did not covary with cognitive-perceptual style, suggesting a dissociation between linguistic prediction and non-linguistic temporal dynamics. Finally, in a separate experiment (N = 28, age 21–41), individuals with more ASD-like profiles showed reduced adaptation to latent-state volatility in a voice detection task, especially with increasing age. These findings demonstrate the ASD–SSD continuum to provide a dynamic, lifespan-sensitive framework for understanding individual differences in perceptual inference and predictive processing.

INTRODUCTION

Perception is a deeply subjective process, shaped not only by the stimuli we encounter, but also by the unique cognitive state of the perceiver. From a Bayesian perspective, perception arises from a dynamic balance between prior expectations and incoming sensory evidence. Depending on where one places emphasis – on (potentially inaccurate) prior beliefs or on (potentially noisy) sensory evidence – different perceptual outcomes might emerge (see Fig. 1a).

This raises several questions central to the present study: First, can we measure inter-individual differences in how individuals weigh prior knowledge against incoming sensory evidence? Second, how do such individual strategies develop across the adult lifespan, given known age-driven changes in sensory precision and cognitive flexibility (Hartshorne & Germine, 2015; Heckner et al., 2021; Lindenberger & Ghisletta, 2009; Salthouse, 2009; Salthouse et al., 2003)? And third, can individual differences in prior-sensory weighting be meaningfully captured and employed to investigate predictive processing in different contexts?

The first question can be addressed using a relatively new model of cognitive-perceptual style: the *ASD–SSD continuum*, a framework recently proposed to model individual differences, in both clinical and neurotypical populations, in the weighting of prior knowledge and incoming sensory evidence during perceptual inference (Dinsdale et al., 2013; Tarasi, Martelli, et al., 2023).

Originally developed within theory of mind research (Abu-Akel & Bailey, 2000), the ASD-SSD continuum posits *Autism Spectrum Disorders* (ASD) and *Schizophrenia Spectrum Disorders* (SSD) as diametric opposites in cognitive style – an idea later extended to broader domains of social cognition and information processing (Crespi & Badcock, 2008). According to this view, individual cognitive-perceptual strategies can be positioned along a continuum ranging from ASD-like to SSD-like cognition and perception (Dinsdale et al., 2013).

What renders the ASD–SSD continuum particularly valuable for psychological research is its applicability beyond clinical populations. Indeed, it is thought to reflect a continuous dimension of cognitive-perceptual variation that also exists within the neurotypical population. Even among healthy individuals, subtle differences in cognitive-perceptual style, ranging from more prior-driven to more sensory-driven perceptual processing, can be measured and modelled (e.g., see Marsicano & Melcher, 2025; Tarasi, Borgomaneri, et al., 2023; Tarasi, Martelli, et al., 2023). This renders the continuum a powerful tool for investigating individual differences in perception and cognition beyond clinical diagnosis.

At the ASD end of the continuum, perception is typically characterised by heightened attention to detail (Baron-Cohen et al., 2001), strong systemising tendencies (Baron-Cohen, 2009), and an overweighting of sensory evidence relative to prior knowledge due to ineffective feedback signalling and/or over-expression of prediction errors (Andersen, 2022; Tarasi, Martelli, et al., 2023; Tarasi, Trajkovic, et al., 2022). In contrast, SSD-like perception is associated with an increased susceptibility to hallucinations and delusions, heightened cognitive disorganisation (Abu-Akel et al., 2022; Andersen, 2022; Raine, 1991) as well as a strong reliance on prior knowledge – potentially caused by hyper-signalling of prior information from high-level regions to earlier sensory areas (Tarasi, Trajkovic, et al., 2022; see Fig. 1a). This diametric relationship between ASD and SSD is further supported by findings by Zhou et al. (2019), demonstrating an inverse correlation between positive schizotypal and autistic traits.

For instance, the individual score on the ASD-SSD continuum (the *ASD-SSD score*) has shown behavioural and neural correlates in perceptual inference tasks. Individuals with higher ASD–SSD (i.e., more SSD-like) scores were more strongly influenced by predictive cues, as reflected by stronger cue-related modulation of pre-stimulus alpha power. In contrast, individuals with lower (i.e., more ASD-like) scores were interpreted to rely more on incoming sensory evidence later in the trial (Tarasi, Martelli, et al., 2023). In line with this, a study by Marsicano and Melcher (2025) found that participants with more SSD-like traits showed a greater bias toward assuming serial dependencies between events, indicating a heightened influence of perceptual history on their processing. Conversely, individuals at the opposite end of the continuum – those with a more ASD-like cognitive-perceptual style – exhibited a reduced bias toward serial dependencies, suggesting a stronger reliance on present compared to past sensory evidence.

Taken together, previous findings support the idea that the ASD–SSD continuum captures trait-like differences in how individuals integrate top-down and bottom-up information, that is, their individual cognitive-perceptual style.

Traditionally, ASD–SSD scores are derived from two self-report instruments: the 50-item Autism Spectrum Quotient (AQ; Baron-Cohen et al. 2001) and the 74-item Schizotypal Personality Questionnaire (SPQ; (Raine 1991)). PCA-based approaches yield continuous positions along the continuum (Tarasi, Borgomaneri, et al., 2023; Tarasi, Martelli, et al., 2023), while k-means clustering produces discrete subtypes (Abu-Akel et al., 2017; Marsicano & Melcher, 2025). While clustering may facilitate interpretability by defining clear subtypes, it inherently reduces dimensional variability

to categorical labels, risking loss of nuanced information and imposing arbitrary boundaries on what is theoretically a continuous dimension. The AQ's subscale and scoring structure remain debated, with at least 14 alternative models proposed (Austin, 2005; do Egito et al., 2018; Freeth et al., 2013; Hoekstra et al., 2008, 2011; Hurst et al., 2007; Kloosterman et al., 2011; W. Y.-P. Lau et al., 2013; Leth-Steensen et al., 2021; Russell-Smith et al., 2011; Stewart & Austin, 2009; Zhu et al., 2022). In contrast, the SPQ's nine subscales are well established.

Previous studies on the ASD–SSD continuum have laid important groundwork for modelling individual differences in cognitive-perceptual style. However, several methodological limitations are worth noting. Most importantly, the samples tested in previous studies tend to be highly homogenous, typically consisting of young university students – with the sole exception of two studies (Marsicano & Melcher, 2025; Tarasi, Borgomaneri, et al., 2023), where more age-diverse participants from the general population were recruited. As a result, it remains unclear whether these effects generalise beyond university settings, and it is not possible to model potential age-related effects.

In the present study, we propose and validate a revised, more psychometrically sound approach to estimating individual ASD-SSD scores, examine their association with age, and demonstrate how they can be employed to model perceptual processing in three psychological experiments.

First, we compared the traditional approach of calculating ASD-SSD scores using a binary item-scoring system and the five-subscale structure as introduced by Baron-Cohen et al. (2001) and used in the studies by Tarasi et al. (Tarasi, Borgomaneri, et al., 2023; Tarasi, di Pellegrino, et al., 2022; Tarasi, Martelli, et al., 2023) with a more modern approach based on the suggestions by English et al. (2020), using a 4-point item-scoring system (Austin, 2005) and (a) the 3-factor model by Russel-Smith et al. (2011), and (b) the 5-factor model by Kloosterman et al. (2011). For the SPQ, we retained the full set of nine original subscales.

Second, to examine age-related changes in cognitive-perceptual style, we modeled ASD-SSD scores as a function of chronological age. Previous studies have shown that across sensory modalities, older adults rely more heavily on prior expectations (Brown et al., 2022; Chan et al., 2021; Milburn et al., 2023; Parthasharathy et al., 2022; Schuckart et al., 2024; Wolpe et al., 2016), which has been interpreted as a compensatory mechanism in response to age-related declines in executive

functioning and sensory precision (Karmali et al., 2018; Schuckart et al., 2024). We therefore hypothesised that this shift would be reflected in individual cognitive-perceptual style, with older adults displaying a more SSD-like, prior-driven mode of perceptual inference compared to younger individuals.

Third, to demonstrate the validity of our refined ASD-SSD scores and how they can be used to disentangle age-related effects from differences in cognitive-perceptual style (i.e., prediction tendencies), we analysed word-level reading times in a self-paced reading task. We hypothesised that individuals with a more sensory-driven, ASD-like processing style would show increased sensitivity to incoming evidence, thereby reacting more strongly to variations word predictability than their peers (see Fig. 1b, upper panel). Additionally, building on previous findings (Schuckart et al., 2024), we explored how this potential interaction of word predictability and cognitive perceptual style might be modulated by age. In our previous study (Schuckart et al., 2024), sensitivity to differences in word surprisal (i.e. the inverse of word predictability) was strongest in older adults. Here, we tested whether this effect can be partially or fully explained by individual differences in cognitive-perceptual style.

Fourth, we examined autocorrelations of residualised (i.e. non-lexically driven) reading times, to test whether cognitive-perceptual style is reflected in the temporal dynamics of response patterns more generally. Autocorrelations capture the extent to which a time-series variable correlates with itself across different lags – that is, how strongly current values relate to their past counterparts. Typically, autocorrelations decline with increasing lag (Baayen & Milin, 2010), reflecting the general tendency for more distant events in the time series to exert weaker influence. The present study thus aimed to investigate how individual differences in cognitive-perceptual style might relate to patterns in autocorrelations of residualised, non-lexically modulated response times. In line with the literature (Marsicano & Melcher, 2025), we hypothesised that a more prior-driven, SSD-like processing style would manifest in steadier response rhythms – reflected by higher autocorrelations that gradually decay across lags – whereas a more sensory-driven, ASD-like style would result in more variable response times and thus overall flatter autocorrelation profile (see Fig. 1b, lower panel).

Finally, we explored whether the ASD-SSD continual cognitive-perceptual style reflects in the way an individual responds to changing latent-state volatility in an auditory perceptual experiment detecting human voice sounds occurring at an unknown, and changing, rate.

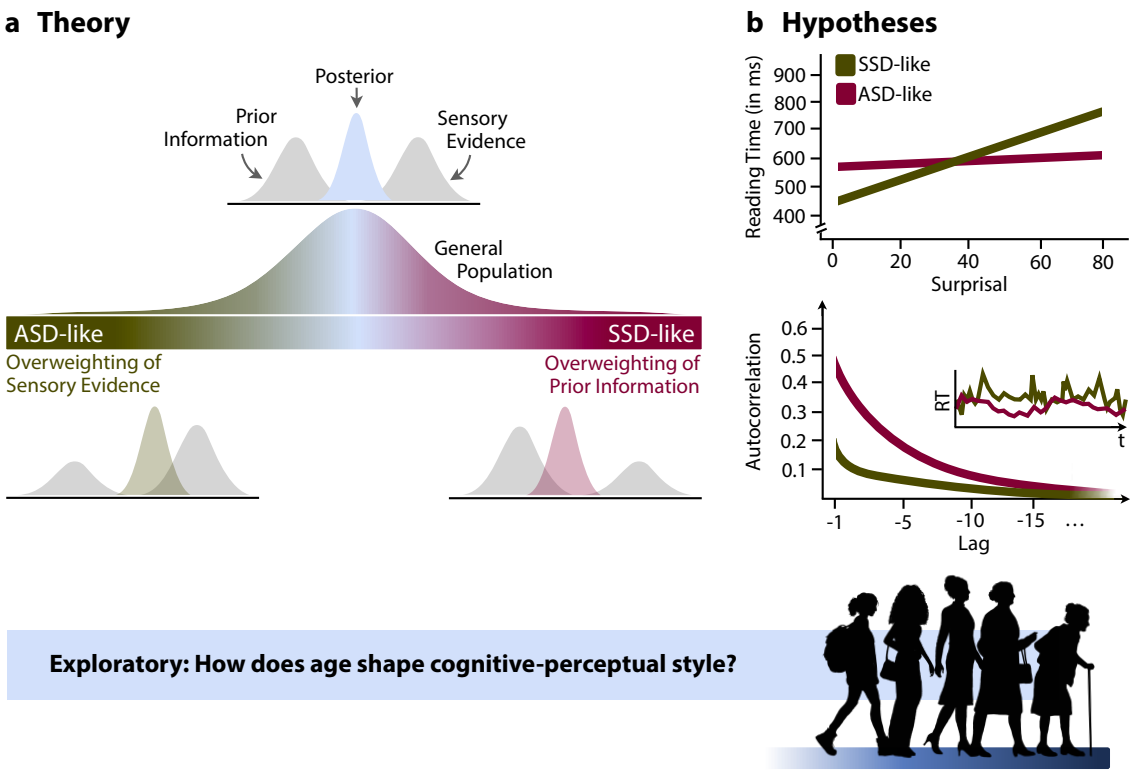

Figure 1. Overview of the theoretical background of the ASD-SSD continuum and the hypotheses tested in the present study. a) Weighting of prior information and sensory evidence across the ASD-SSD continuum. Low scores on the ASD-SSD continuum correspond to more sensory-driven, ASD-like cognitive perceptual style, which is characterised by overweighting of sensory evidence. High scores on the ASD-SSD continuum reflect prior-driven, SSD-like cognitive-perceptual processing with less reliance on sensory evidence and more reliance on prior information. b) We hypothesised more sensory-driven, ASD-like processing would result in a higher susceptibility to changes in the stimulus material (i.e., strong word surprisal effects; see green line in the upper panel) than individuals with more SSD-like processing style (see pink line). In line with this, we hypothesised individuals with a more sensory-driven, ASD-like processing style would also exhibit more variability in their residualised, non-lexically driven reading times (see more variable response times shown in green in the lower panel inset), resulting in an overall flatter response time autocorrelation profile. In addition, we explored how age might shape cognitive-perceptual style more broadly, and how these age-related differences may help further explain patterns observed in our reading time data. RT = reading time.

RESULTS

Revised ASD–SSD Scoring Method Validated Against Established Models

In all six studies, participants were asked to complete both the 50-item version of the AQ (Baron-Cohen et al., 2001) and the 74-item version of the SPQ (Raine, 1991) to assess subclinical autistic and schizotypal traits, respectively.

For the SPQ, we employed the original item scoring and 9-factor model by Raine (1991). However, for the AQ, subscale scores were derived using three different methods:

First, we applied the five "classic" subscales proposed by (Baron-Cohen et al., 2001) and used in the studies by Tarasi et al. (Tarasi, Borgomaneri, et al., 2023; Tarasi, di Pellegrino, et al., 2022; Tarasi, Martelli, et al., 2023; Tarasi, Trajkovic, et al., 2022). For this, we applied the original item scoring method in which the 4-point Likert scale is collapsed into a binary format (Baron-Cohen et al., 2001). Additionally, we also computed AQ subscale scores using two more recent, alternative factor models as suggested by English et al. (2020): the three-subscale system by (Russell-Smith et al., 2011), and the five-subscale system by (Kloosterman et al., 2011), in both cases using the alternative 4-point scoring of items as proposed by Austin (2005). A complete item-to-subscale mapping for both SPQ and AQ questionnaire is provided in the supplementary materials (see Tables S1 and S2).

Prior to further analyses, we assessed the factorability of the correlation matrices underlying combinations of SPQ subscale scores with AQ subscale score derived from three different factor models: Baron-Cohen, Russell-Smith, and Kloosterman. For this purpose, we computed the *Kaiser-Meyer-Olkin Measure of Sampling Adequacy* (KMO-MSA; Kaiser, 1974) as well as *Bartlett's Test of Sphericity* (Bartlett, 1937).

Bartlett's test was significant for all three combinations of SPQ and AQ subscales (SPQ and Baron-Cohen-based AQ: $\chi^2(91) = 1986.059$, $p < .001$; SPQ and Russel-Smith-based AQ: $\chi^2(66) = 1618.067$, $p < .001$; SPQ and Kloosterman-based AQ: $\chi^2(91) = 1883.072$ $p < .001$), indicating that the subscales showed sufficient intercorrelation to proceed with principal component analysis.

However, the KMO-MSA results revealed insufficient sampling adequacy for the Russel-Smith based AQ subscales: the three AQ subscales yielded individual MSAs of 0.60 (RS-SS), 0.77 (RS-DP), and 0.46 (RS-CM), with two out of three falling below the commonly accepted threshold of 0.60 (Kaiser, 1974), suggesting limited shared variance with the remaining subscales. In contrast, sampling adequacy was acceptable for the other two models. For the Baron-Cohen-based AQ subscales, individual MSAs

ranged from 0.65 to 0.82, with an overall MSA of 0.78. For the Kloosterman model, AQ subscale MSAs ranged from 0.72 to 0.80, with an overall MSA of 0.80.

Across all three models, SPQ subscales consistently showed good sampling adequacy, with individual MSAs averaging 0.807 ± 0.057. The lowest SPQ MSA was found for the subscale Odd Beliefs or Magical Thinking (OB; range of MSAs: 0.68 – 0.69), and the highest one for Odd or Eccentric Behaviour (OBH; range of MSAs: 0.87 – 0.89).

Taken together, as KMO-MSA results indicated acceptable factorability only for the Baron-Cohen and Kloosterman models, we limited subsequent analyses to comparisons based on the Baron-Cohen- and Kloosterman-based AQ subscales and their corresponding ASD-SSD scores.

Following these factorability checks, we conducted two *Principal Component Analyses* (PCA) to derive loadings for weighting AQ and SPQ subscales in the computation of individual ASD-SSD scores. One PCA included all SPQ subscales along with the Baron-Cohen-based AQ subscales; the other combined SPQ subscales with the Kloosterman-based AQ subscales. While PC1 in both PCAs failed to capture any distinction between ASD- and SSD-like subscales, the second principal component (PC2) discriminated between ASD- and SSD-like cognition and perception (see Fig. 2b and c), with an explained variance of 17% as compared to 20.9% of explained variance reported by (Tarasi, Martelli, et al., 2023; see Fig. 2d). A complete overview of all subscale loadings is provided in Table S3.

The loading patterns we obtained for the second principal component (PC2) of the first PCA – computed using SPQ and Baron-Cohen-based AQ subscales – closely mirrored those reported by Tarasi et al. (computed from questionnaire data of N = 80 young participants using the same subscales). Specifically, the AQ subscales poor *Social Skills* (SS), poor *Attention Switching* (AS), poor *Communication* (C), and poor *Imagination* (I), as well as the SPQ subscales *Social Anxiety* (SA), *No Close Friends* (NCF) and *Constricted Affect* (CA), loaded in the same direction. In contrast, the AQ subscale exceptional *Attention to Detail* (AD) and SPQ subscales *Ideas of Reference* (IR), *Odd Beliefs or Magical Thinking* (OB), *Unusual Perceptual Experiences* (UPE), *Odd or Eccentric Behaviour* (OBH), *Odd Speech* (OS) and *Suspiciousness* (SUS) loaded in the opposite direction.

This pattern supports the interpretation of PC2 as capturing the diametric contrast between ASD- and SSD-like traits: subscales reflecting ASD-like characteristics – such as social withdrawal, cognitive rigidity, and flattened affect –

appear on one end of the component, while those reflecting SSD-like features – such as magical thinking, anomalous belief formation, and perceptual aberrations – cluster on the other.

For the second PCA – computed using SPQ and Kloosterman-based AQ subscales – we found a similarly clear distinction between ASD- and SSD-like traits on the second principal component, with the AQ subscales *Social Skills* (SS), *Communication/Mindreading* (CM), *Restricted/Repetitive Behaviour* (RRB), *Imagination* (I) and *Attention to Detail* (AD) loading in the same direction as the SPQ subscales *Social Anxiety* (SA), *No Close Friends* (NCF) and *Constricted Affect* (CA), whereas the remaining SPQ subscales – *Ideas of Reference* (IR), *Odd Beliefs or Magical Thinking* (OB), *Unusual Perceptual Experiences* (UPE), *Odd or Eccentric Behaviour* (OBH), *Odd Speech* (OS) and *Suspiciousness* (SUS) – loaded in the opposite direction. This loading pattern again reflects the diametric relationship between ASD- and SSD-like styles of perception, cognition, and behaviour.

Employing the extracted loadings of PC2 from the two PCAs (Fig. 2b and c), and the previously published loadings from Tarasi et al. (2023), we computed individual ASD–SSD scores based on three distinct models, summarised in Table 1. This approach enabled us to validate our revised method (model 3; Fig. 2b) against both the original method as implemented here (model 2; Fig. 2c) and a previously published model of the same structure (model 1; Fig. 2d), known to yield robust results in a psychophysical prediction task.

The ASD–SSD scores from the three models correlated highly (models 1 and 2: Spearman's $\rho = 0.910$, $p < 0.001$; models 2 and 3: Spearman's $\rho = 0.938$, $p < 0.001$), confirming the successful implementation of the original method (models 1 and 2) as well as our revised model (model 3) capturing the same underlying construct as the more traditional models 1 and 3. Based on these results and the increased psychometric soundness of our revised model 3 (English et al., 2020), all subsequent analyses employed these revised ASD-SSD scores.

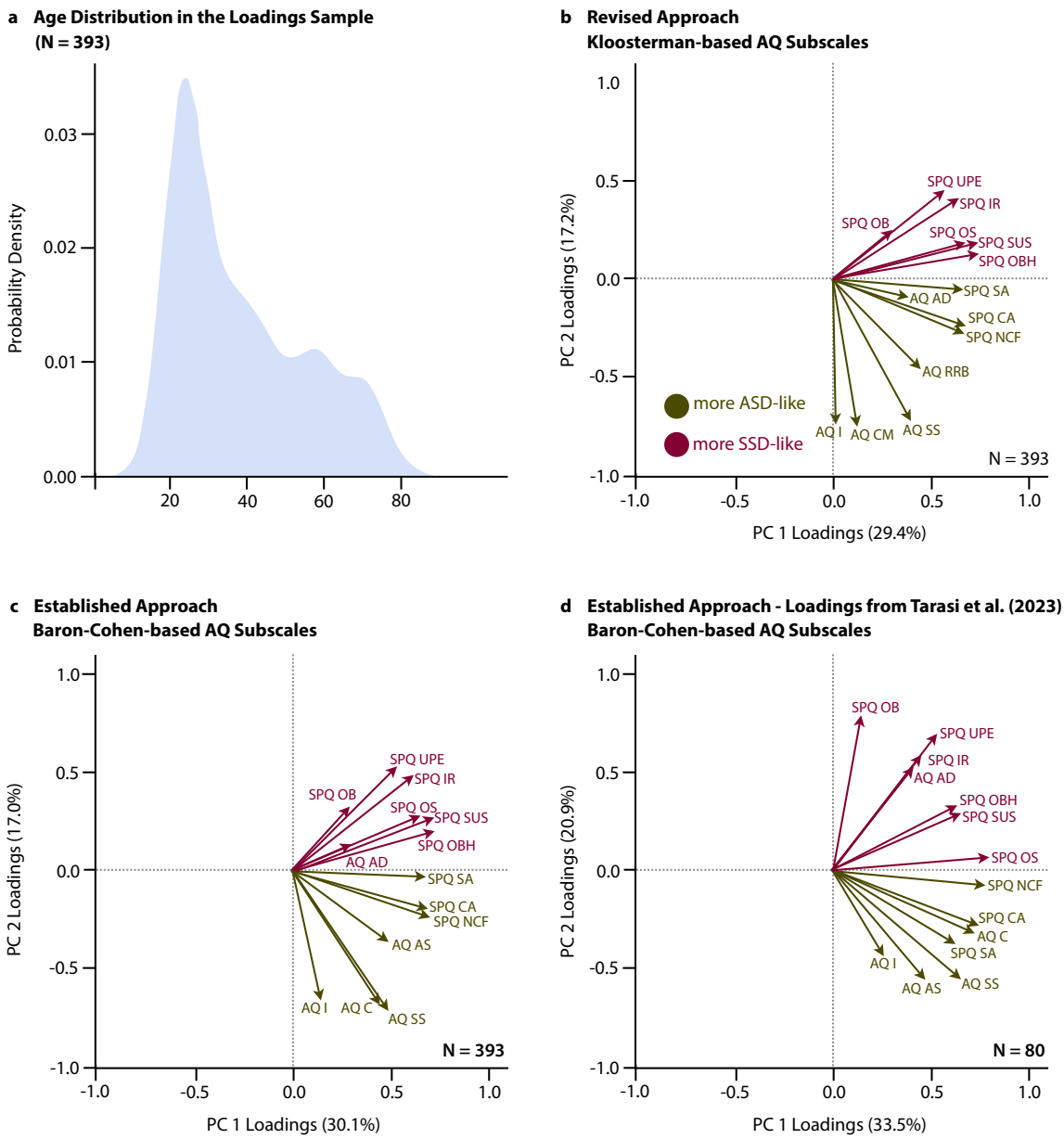

Figure 2. Results of the Principal Component Analyses. Panel **a** depicts the age distribution of the sample used to compute PCA loadings. Panel **b** illustrates the loadings for the first two principal components from the PCA on our revised scoring approach, which employed the AQ factor model proposed by Kloosterman et al. (2011). In contrast, panels **c** and **d** display PCA results from the original ASD-SSD scoring method, which relies on the Baron-Cohen five-subscale AQ model (Baron-Cohen et al., 2001). The loadings in panels **b** and **c** are based on data from our large, age-diverse dataset (N = 393), while panel **d** reproduces the loadings reported by Tarasi et al. (2023), which were computed with data from a smaller sample of young adults (N = 80). For clearer comparison, the loadings in panels **b** and **c** have been sign-flipped to align with those from Tarasi et al. For an overview of AQ and SPQ subscales and their abbreviations please see Tables S1 and S2.

Table 1. Models for computing individual ASD-SSD scores.

Model	SPQ item scoring and factor structure	AQ item scoring	AQ factor structure	Sample for computation of loadings
1	Raine, 1991	Baron-Cohen et al., 2001	Baron-Cohen et al., 2001	N = 80, young (Tarasi et al., 2023)
2	Raine, 1991	Baron-Cohen et al., 2001	Baron-Cohen et al., 2001	N = 393, age-diverse
3	Raine, 1991	Austin, 2005	Kloosterman et al., 2011	N = 393, age-diverse

Demonstrating the Predictive Utility of the Revised ASD–SSD Continuum Scores

In the following sections, we report data from (1) a large pooled sample comprising 340 participants (M_{age} = 38.94 ± 17.11 years, 18-82 years, 59.12% female) who completed the AQ and SPQ questionnaires (sample employed for Analysis 1); (2) a smaller subset of the pooled sample, comprising 247 participants (M_{age} = 42.78 ± 17.35 years; 18-82 years, 55.87% female) who performed a self-paced reading task in addition to completing the two questionnaires (see Fig. 3a; Analyses 2 and 3); and (3) another subset of the pooled sample (N = 28, M_{age} = 28.08 ± 5.69 years, range: 21-41 years, 50% female), who performed an auditory voice vs. non-voice discrimination task under different levels of volatility in the occurrence rate of these stimulus classes. They also completed the AQ and SPQ questionnaires (see Fig. 3b; Analysis 4). Please refer to the *Methods* section for further details.

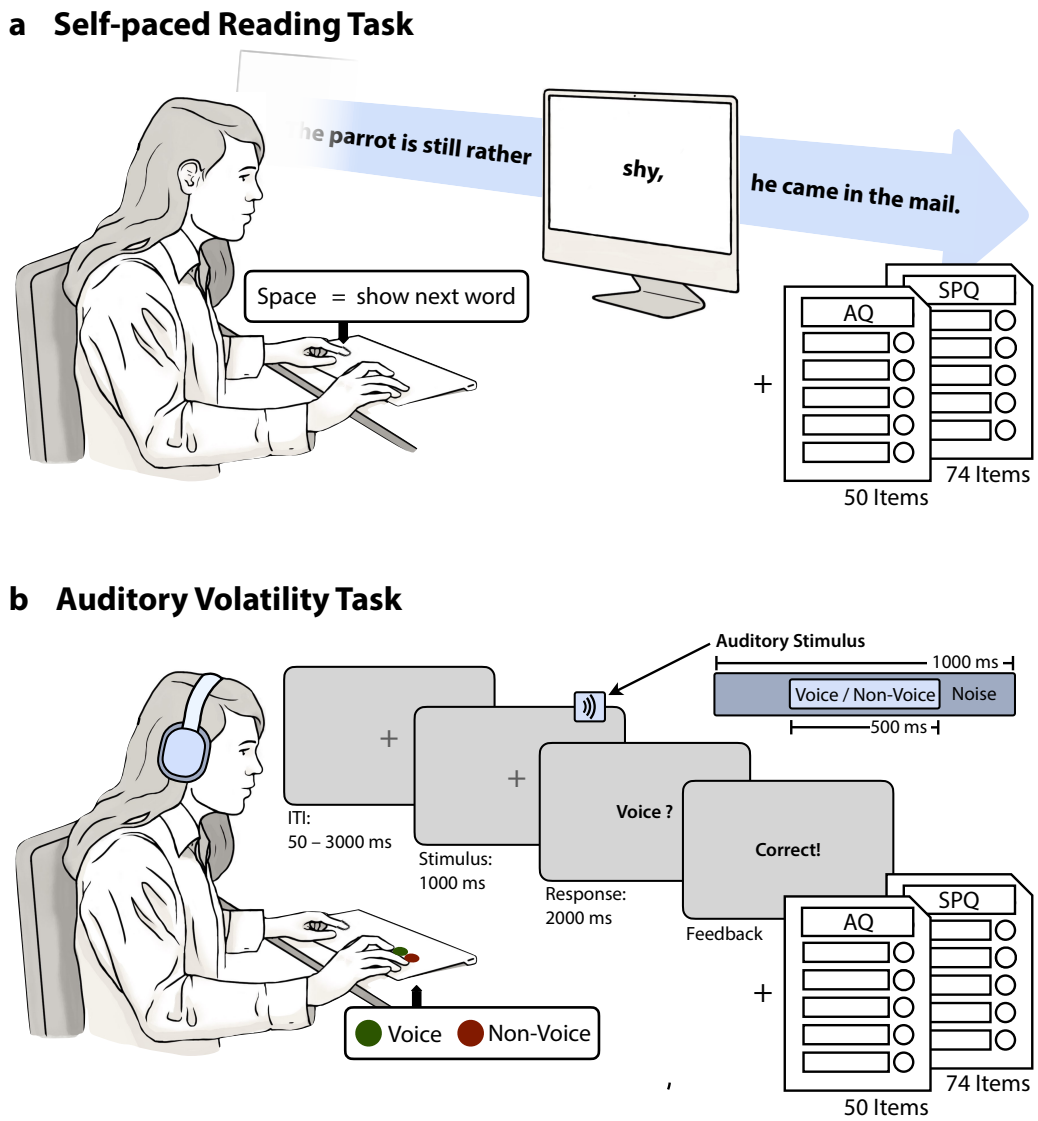

Figure 3. Experimental Designs. Panel **a**: A sample of N = 247 participants completed a self-paced reading task, advancing through text word-by-word by pressing the space bar. Two additional conditions included an orthogonal n-back task to increase cognitive load; however, these conditions are not analysed here and thus not shown. All participants performed either two or three blocks of this baseline reading task, consisting of 300 trials (words) each, depending on which experiment they participated in. Alongside the reading task, participants also completed the two questionnaires AQ and SPQ to assess their individual cognitive-perceptual style. Panel **b**: A smaller subset of participants (N = 28) performed an auditory speech-in-noise detection task under varying levels of volatility. High volatility blocks had frequent changes between voice and non-voice trials (i.e., change probability = 9% after each trial), while low volatility blocks consisted of longer sequences of either voice or non-voice trials (i.e., 1% change probability). Participants indicated via button press whether they heard a voice or a non-voice within a noisy stream. Following each trial, feedback was provided to facilitate learning of the temporal regularities. After completing the auditory task, participants also filled out the Autism-Spectrum Quotient (AQ) and Schizotypal Personality Questionnaire (SPQ).

Advancing Age Predicts Shift Toward ASD-Like Cognitive–Perceptual Style

To assess the influence of demographic factors on ASD–SSD scores in the pooled sample (N = 340, see age distribution in Fig. 4a), we fitted a linear model (LM) including age, years of education, and gender as predictors, alongside a nuisance regressor coding whether participants completed the questionnaire online or in the lab, controlling for a potential social desirability bias.

Results showed a negative effect of age on ASD-SSD scores ($\beta = -0.050$, $t(335.0) = -4.521$, $p < 0.001$; see Fig. 4b). Similarly, self-identified male participants showed lower scores than female participants ($\beta = -1.001$, $t(335.0) = -4.031$, $p < 0.001$; see Fig. 4d), suggesting subtle gender-related differences in cognitive-perceptual style, with male individuals exhibiting more sensory-driven perceptual processing than female individuals. No significant relationship was observed between educational attainment and individual ASD-SSD scores. For full results please see Table 1.

To evaluate the stability of our results, we employed 5-fold cross-validation (Poldrack et al., 2020). Across the five runs, the effects of age and gender consistently reached significance, suggesting that these effects are not overly dependent on specific subsets of the data (see Fig. 4c and 4d, and Table S5). The average root mean squared error (RMSE) was 2.177 ± 0.305, indicating that, on average, predicted ASD-SSD scores deviated from observed scores by approximately 2.18 points on the ASD-SSD continuum. Considering that the LM included only basic demographic predictors (age, education, and gender), this level of prediction error is reasonable and suggests that these variables capture meaningful variance in ASD-SSD scores despite the model's simplicity.

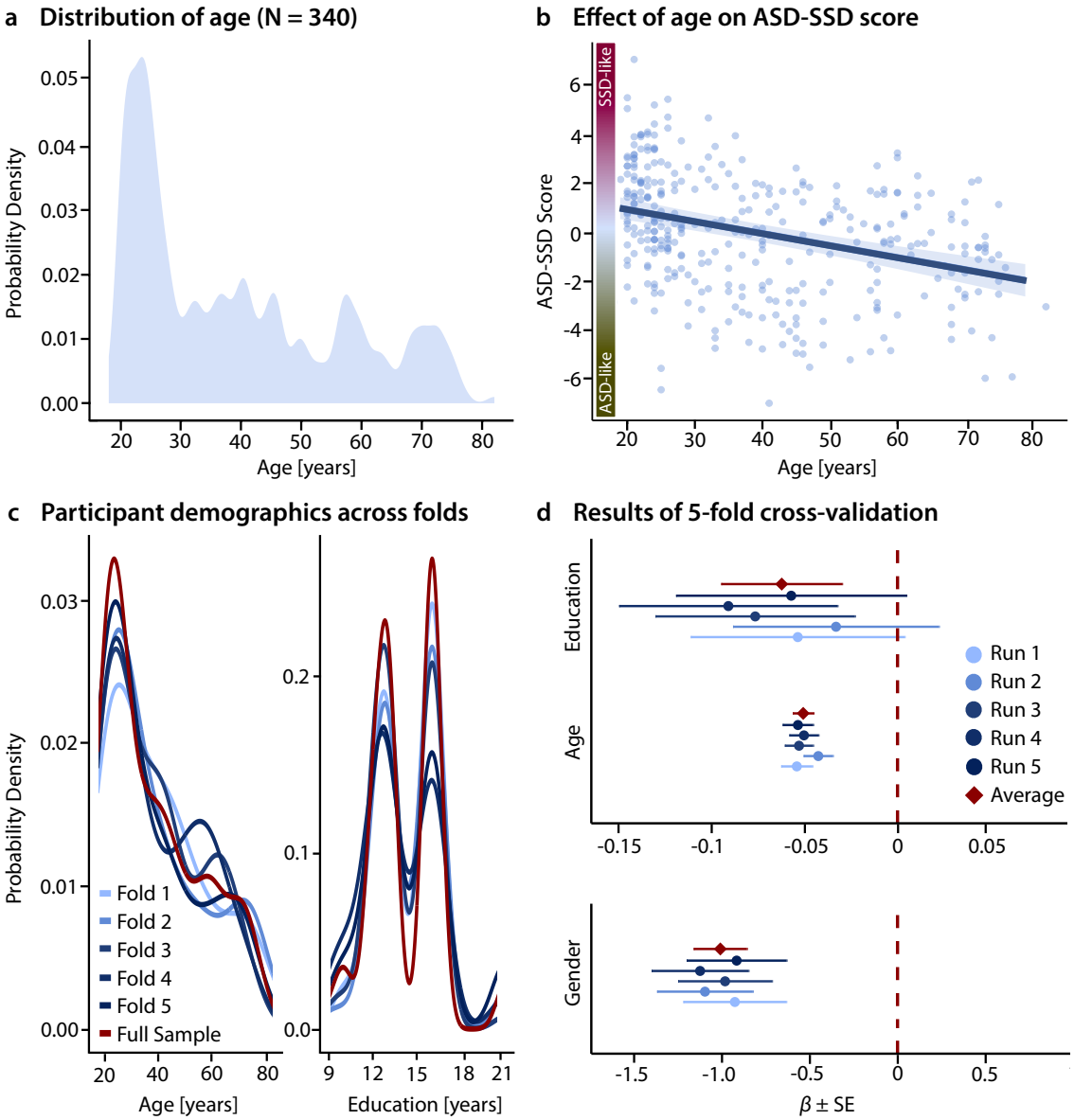

Figure 4. **Effect of age on ASD-SSD scores.** Panel **a** illustrates the distribution of the sample used for the demographic analysis. Note that this sample (N = 340) is smaller than the sample used for computing the loadings (N = 393), as demographic information on age, gender, and education was not available for all participants in the loadings sample. Panel **b** presents the estimated marginal mean for the effect of age, alongside the original data points depicting the relationship between age and ASD-SSD scores. Older participants exhibited significantly lower ASD-SSD scores – indicative of a more sensory-driven processing style – compared to younger participants. Panels **c** and **d** display the results of the 5-fold cross-validation: Panel **c** shows the distributions of age and education in all folds as well as in the original full sample, while panel **d** summarizes the cross-validation results, presenting estimates ± standard errors (SE). Average estimates were calculated across folds. To pool SEs, we averaged the squared SEs (variances) from each fold, added the variance of the estimates across folds adjusted for sample size, and then took the square root to reflect total uncertainty. In each run, the LM was fitted using 80% of the original data.

Table 2. Results for LM for effects of age, education, gender and the presence of an experimenter on individual ASD-SSD scores.

Predictor	*Estimate*	*Std. Error*	*CI*	*t*	*p*	
Presence of experimenter	1.137837	0.275175	0.59655 – 1.67913	4.134957	1.123×10^{-4}	*
age	-0.049552	0.006952	-0.06323 – -0.03588	-7.127959	3.148×10^{-11}	*
education	-0.060111	0.049877	-0.15822 – 0.03800	-1.205180	2.862×10^{-1}	
gender	-1.000972	0.248288	-1.48937 – -0.51257	-4.031492	1.144×10^{-4}	*
N	340					
df	335.0					
R2 / R2 adjusted	0.230 / 0.221					

Note. All continuous predictors were centred. Degrees of freedom for p-values and confidence intervals (CI) were computed using Wald's approximation. All p-values reported here are FDR-corrected and were computed using ANOVAs with type III sum of squares. Results that are significant on an alpha level of 0.05 are marked with an asterisk.

To get a more nuanced grasp of the effect of age on ASD-SSD score, we conducted an exploratory linear model analysis comprising centred AQ and SPQ subscale scores as predictors and log-transformed age as the dependent variable. Results revealed that age was negatively associated with self-reported symptom severity on several SPQ subscales, including *Ideas of Reference* (IR), *Social Anxiety* (SA), and *Unusual Perceptual Experiences* (UPE), as well as on the AQ subscale *Repetitive or Restricted Behaviour* (RRB).

In contrast, age was positively associated with SPQ subscale *Odd Beliefs or Magical Thinking* (OB), as well as with AQ subscales reflecting difficulties in *Imagination* (I) and *Social Skills* (SS; see main results in Table 2 and full results in Table S4).

To assess the influence of these changes in subscale scores on the ASD-SSD continuum, it is necessary to also assess the subscales' loadings on the ASD-SSD Principal Component (see Table S3). The SPQ subscales all exhibit relatively low absolute loadings on the ASD-SSD component (M = 0.242 ± 0.128), whereas AQ subscales show markedly higher loadings (M = 0.535 ± 0.282). Notably, the *Social Skills* subscale contributes disproportionately to the ASD-SSD score, with a particularly high loading towards the ASD pole (loading: 0.706). This implies that changes in AQ

subscales – especially Social Skills – exert a stronger influence on the ASD-SSD score than changes in SPQ subscales.

With regard to our findings, this means that an age-related decline in social skills substantially increases the ASD-SSD score by shifting it toward the ASD pole. At the same time, reductions in symptom severity for SPQ subscales like *Unusual Perceptual Experiences* (loading: -0.455) and *Ideas of Reference* (–0.415) also contribute to this shift, by reducing the overall SSD-related symptom strength. Hence, the observed negative association between age and ASD-SSD scores – i.e. the shift toward a more ASD-like cognitive-perceptual style – likely reflects a combination of poorer social functioning and fewer perceptual or referential anomalies.

Table 3. Associations of AQ and SPQ subscales with age.

Predictor	***Estimate***	***Std. Error***	***CI***	***t***	***p***	
AQ I (poor Imagination)	0.029906	0.008306	0.013567 – 0.046245	3.600662	**2.749×10^{-3}**	*
AQ SS (poor Social Skills)	0.022391	0.006422	0.009757 – 0.035025	3.486574	**2.779×10^{-3}**	*
AQ RRB (Repetitive/Restricted Behaviour)	-0.024728	0.009537	-0.043490 – -0.005965	-2.592691	**3.135×10^{-2}**	*
SPQ IR (Ideas of Reference)	-0.033796	0.014352	-0.062028 – -0.005563	-2.354841	**4.719×10^{-2}**	*
SPQ SA (Social Anxiety)	-0.026523	0.011527	-0.049200 – -0.003847	-2.300927	**4.719×10^{-2}**	*
SPQ OB (Odd Beliefs / Magical Thinking)	0.046600	0.018095	0.011004 – 0.082197	2.575352	**3.135×10^{-2}**	*
SPQ UPE (Unusual Perceptual Experiences)	-0.040471	0.018157	-0.076191 – -0.004752	-2.228910	**4.968×10^{-2}**	*

Note. Main Results from a LMM for age (N = 340). All continuous predictors were centred. The dependent variable age was log-transformed prior to fitting. Degrees of freedom for *p*-values, standard errors and confidence intervals (CI) were computed using Wald's approximation. All *p*-values reported here are FDR-corrected and were computed using ANOVAs with type III sum of squares. Results that are significant on an alpha-level of 0.05 are marked with an asterisk. Please note AQ subscales are based on the Kloosterman et al. (2011) factor structure. Subscale scores were not weighted by loadings for this analysis. For full results please see Table S4.

Age and Sensory-Driven Processing Style Amplify Sensitivity to Lexical Surprisal

To examine how predictive processing during self-paced reading varies along the ASD-SSD continuum, we fitted a linear mixed model (LMM) for word-level reading times, including individual ASD-SSD scores alongside established demographic, lexical, and experiment-specific predictors. The effects of age and word surprisal on reading time were not novel findings: both have already been reported in a previous study (Schuckart et al., 2024), and the current analysis is based on a subset of the original dataset. As such, these results do not constitute a replication but simply reflect the re-inclusion of known predictors in an expanded model.

Consistent with our previous findings (Schuckart et al., 2024), we found that participants read more slowly with increasing age (β = 0.006, t(239.40) = 7.825, p < 0.001) and word surprisal (β = 0.001, t(3333.63) = 7.504, p < 0.001), and that age amplified the effect of surprisal (β = 0.0002, t(161362.62) = 13.886, p < 0.001; see Fig 5a, left panel). In short, advancing age boosted surprisal effects, suggesting that older adults are more susceptible to prediction errors during language processing – a pattern we discuss in more detail in our previous study.

The novel contribution of this model lies in the inclusion of individual ASD-SSD scores as a predictor. Overall, higher ASD-SSD scores were associated with increased reading times (β = 0.013, t(239.32) = 2.284, p = 0.028), indicating individuals with a more prior-driven processing style read more slowly than those who rely more heavily on incoming sensory input. Interestingly, higher word surprisal exerted a stronger effect on reading time in individuals with a more sensory-driven perceptual style (i.e., lower ASD-SSD scores; β = −0.0002, t(161141.90) = −5.999, p < 0.001; see Fig. 5a, right panel). This effect was further amplified by age: a significant three-way interaction between age, surprisal, and ASD-SSD score (β = −0.00001, t(160734.68) = −4.004, p < 0.001) revealed that older adults at the sensory-dominant end of the continuum were particularly sensitive to changes in word surprisal (see Fig. 5b and Table 4, as well as Table S6 for full results).

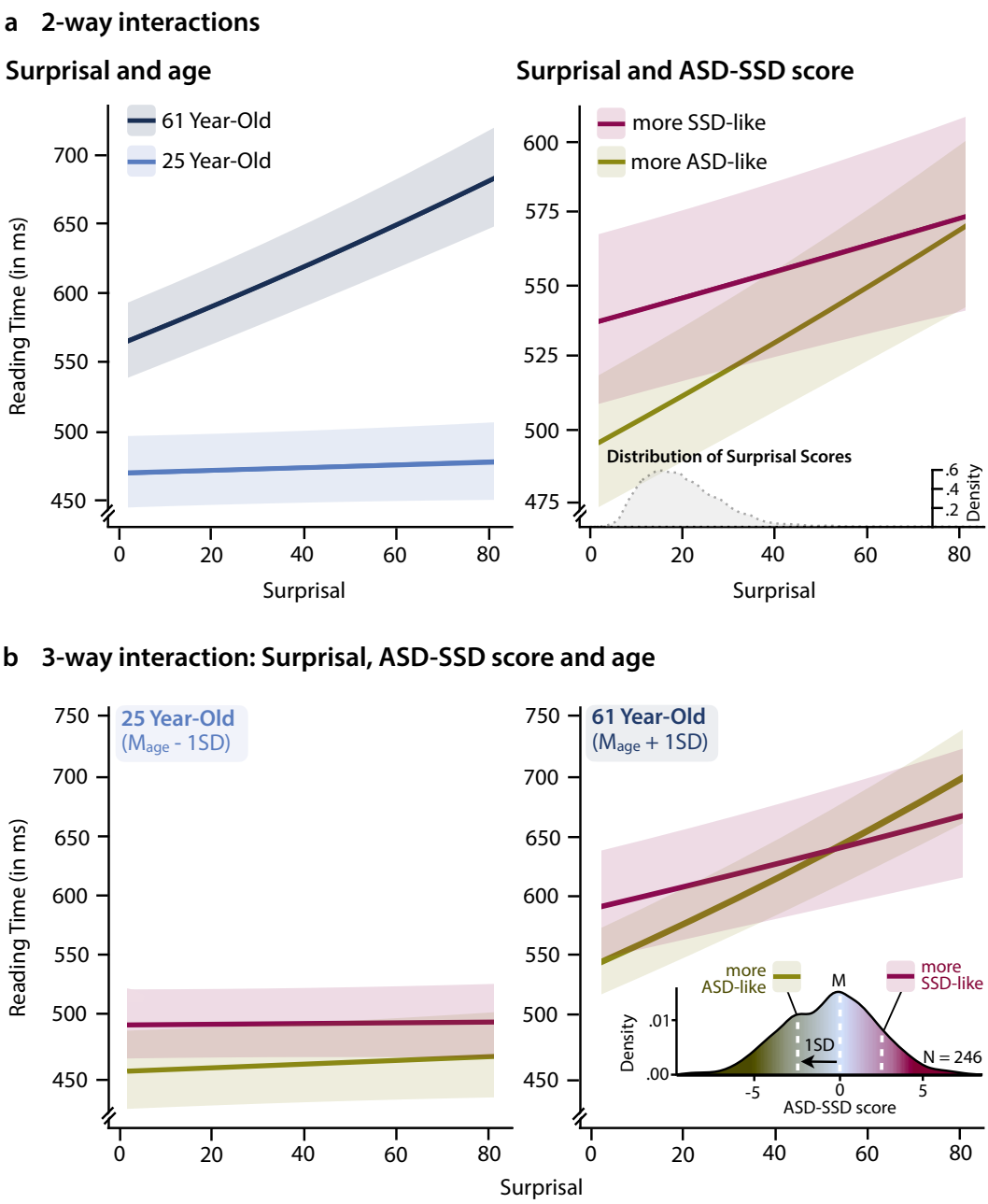

Figure 5. Estimated marginal effects of predictors surprisal, ASD-SSD score and age on word-level reading time. The left plot of panel **a** illustrates the effect of surprisal on reading time in a modelled younger individual (mean age –1 SD, corresponding to 25 years of age in our sample) and older individual (mean age +1 SD; 61 years), which is more pronounced in older individuals. The right plot in panel **a** contrasts surprisal effects between individuals with more sensory-driven, ASD-like (mean ASD-SSD score – 1SD) versus more prior-driven, SSD-like (mean ASD-SSD score + 1SD) cognitive-perceptual styles, indicating generally longer reading times and an attenuated surprisal effect for the latter. Panel (**b**) shows how age modulates the interaction between surprisal and ASD-SSD score on reading time: In younger individuals (left panel), surprisal effects are generally low and largely unaffected by cognitive-perceptual style, with only slightly stronger surprisal effects in individuals with more ASD-like processing. In older individuals (right panel), this pattern is amplified, with surprisal sensitivity increasing markedly in both groups, especially in those with a more ASD-like processing style. The inset illustrates the distribution of ASD-SSD scores in the sample (N = 247) and the M ± 1SD cut-offs used for the modelling contrasts.

Table 4. Central results of the LMM for reading times.

Predictor	Estimate	Std. Error	CI	t	p		df
surprisal	0.001293	0.000172	0.000955 – 0.001631	7.503810	1.581×10^{-13}	*	3333.63
age	0.006313	0.000807	0.004724 – 0.007903	7.825449	2.919×10^{-13}	*	239.40
ASD-SSD	0.012846	0.005625	0.001765 – 0.023926	2.283781	2.791×10^{-2}	*	239.32
surprisal × age	0.000061	0.000004	0.000052 – 0.000069	13.886055	2.447×10^{-43}	*	161362.62
surprisal × ASD-SSD	-0.000193	0.000032	-0.000256 – -0.000130	-5.999267	3.250×10^{-9}	*	161141.90
age × ASD-SSD	-0.000148	0.000347	-0.000831 – 0.000536	-0.425008	6.712×10^{-1}		239.28
surprisal × age × ASD-SSD	-0.000008	0.000002	-0.000011 – -0.000004	-4.004004	8.627×10^{-5}	*	160734.68
N	247						
Intra-class Correlation (ICC)	0.48						
Marginal R^2 / Conditional R^2	0.489 / 0.736						

Note. All continuous predictors were centred. Degrees of freedom for *p*-values, standard errors and confidence intervals (CI) were computed using Satterthwaite's approximation. All *p*-values reported here are FDR-corrected and were computed using ANOVAs with type III sum of squares. Results that are significant on an alpha-level of 0.05 are marked with an asterisk. For full results, please see Table S6.

Serial Response Time Dependencies Are Unrelated to Cognitive-Perceptual Style

In addition to examining reaction times from the self-paced reading task, we also computed autocorrelations of residualised reading times – that is, reading times after statistically controlling for lexical influences alongside some demographical and experimental nuisance regressors using a linear mixed-effects model. These residualised RTs were moderately correlated with the original, unresidualised RTs ($r = 0.517$, $p < 0.001$), indicating that the selected predictors explained a substantial proportion of the variance, while preserving individual variability. The model showed good explanatory power (marginal $R^2 = 0.390$; conditional $R^2 = 0.737$), supporting the validity of the residualisation.

We averaged autocorrelation functions across blocks to derive participant-level profiles, then applied PCA to uncover latent structure (see Fig. 6a). K-means clustering on the first two PCs assigned participants to groups with similar autocorrelation patterns, corresponding to two our hypothesised patterns for ASD- and SSD-like processing. As anticipated, the clustering solution recovered the two expected patterns (see Fig. 6b), with the majority of participants exhibiting a canonical decaying autocorrelation structure (Cluster 1: N = 172; Cluster 2: N = 75) .

However, when statistically comparing the two dominant clusters – those with flat versus decaying autocorrelations – using a linear model, we found no significant differences in ASD-SSD scores ($\beta_{\text{clust1 vs clust2}}$ = 0.335, SE = 0.346, t(245.0) = 0.967, p = 0.344; see Inset in Fig. 6b). While Bayesian model comparison (BF_{10} = 9.817) suggests strong evidence in favour of a model including the autocorrelation cluster as a predictor of individual ASD-SSD score, this result warrants caution. The model explains virtually no variance ($R^2 < 0.001$), and the effect size is negligible, with a wide 95% confidence interval of -0.347–1.017. Given the unbalanced cluster sizes (N = 172 vs. 75; see inset in Fig. 6b), the elevated Bayes Factor may reflect a consistent yet practically irrelevant mean difference in ASD-SSD scores between clusters.

Taken together, our results suggest that, contrary to our initial hypothesis, the emergence of these distinct temporal patterns in reading times cannot be readily explained by individual differences in cognitive-perceptual style along the ASD-SSD continuum. Instead, these fluctuations may reflect a more general feature of processing dynamics, independent of where individuals fall on this dimension.

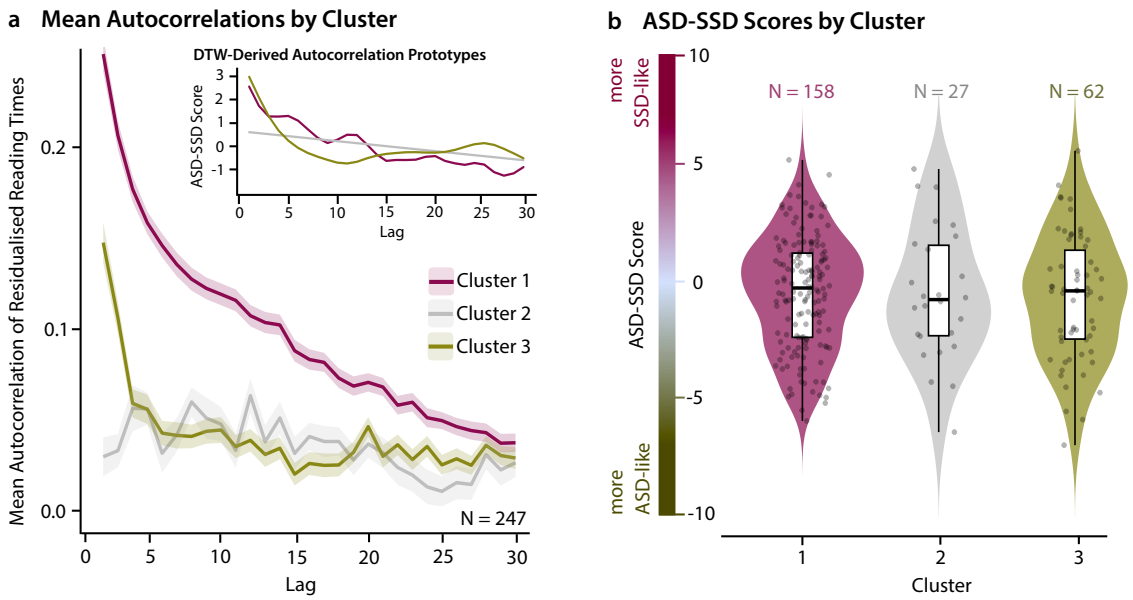

Figure 6. Clustering of autocorrelations derived from residualised reading times across lags *n–2* to *n–30*. Panel **a** shows the loadings for the first two principal components of a PCA on participant-level autocorrelations, with numbers on the arrows indicating the corresponding lag. Panel **b** shows the average autocorrelation trajectories for each of the two clusters identified via k-means clustering. Cluster 1 displays the highest autocorrelations with a smooth, gradual decline across lags, while cluster 2 is marked by elevated short-lag autocorrelations that flatten at longer lags. The inset in panel **b** depicts ASD-SSD scores by cluster, indicating no significant differences in cognitive-perceptual style between the two clusters ($\beta_{\text{clust1 vs clust2}}$ = 0.335, SE = 0.346, t(245.0) = 0.967, p = 0.344, N = 247).

Volatility Preferences Diverge Along the ASD–SSD Continuum

To further validate our revised approach of computing individual ASD-SSD scores, we examined how behavioural sensitivity to latent-state volatility varies as a function of individual ASD-SSD scores and age in a smaller laboratory sample (N = 28, mean age = 28.1 ± 5.7 years). In the corresponding experiment, adapted from Erb et al. (2020), participants judged whether human voices were present in auditory scenes presented under stable (i.e. predictable) or volatile (i.e., unpredictable) base-rate conditions.

A generalized linear mixed-effects model revealed that under low volatility, individuals scoring low on the ASD-SSD continuum – reflecting a more sensory-driven, ASD-like processing style – demonstrated higher response accuracy compared to those with higher scores, suggesting superior performance in stable, predictable environments. Intriguingly, this relationship reversed in high-volatility conditions, where individuals with a more SSD-like, prior-driven processing style exhibited greater accuracy ($OR = 1.077$, $z = 2.913$, $p = 0.009$; see Fig. 7a and Table S8 for full results). Together, these findings imply that stable, low-volatility contexts favour individuals with sensory-driven cognitive-perceptual styles, whereas those with prior-driven styles benefit from environments characterized by greater volatility.

In line with this, a mixed-effects analysis revealed that while individuals exhibiting more ASD-like, sensory-driven perceptual processing exhibited shorter response times (i.e. higher task performance) under low than under high volatility, this pattern was reversed in participants with more SSD-like profiles ($\beta = -0.029$, $t(10034.4) = -5.404$, $p < 0.001$; see Table S7 for full results).

Interestingly, this interaction of cognitive perceptual style and volatility was particularly pronounced with increasing age (3-way interaction of cognitive-perceptual style, volatility and age; $\beta = -0.004$, $t(10034.45) = -3.922$, $p < 0.001$; see Fig. 7b, right panel). Although the sample was small and consisted mostly of participants in their twenties (mean age = 28.08 ± 5.69, range: 21–41), these early patterns hint at a dynamic interplay between age, perceptual style, and environmental volatility. Additionally, these findings provide initial validation that the ASD-SSD continuum is predictive of how individuals adapt to environmental volatility – a key feature of perceptual inference.

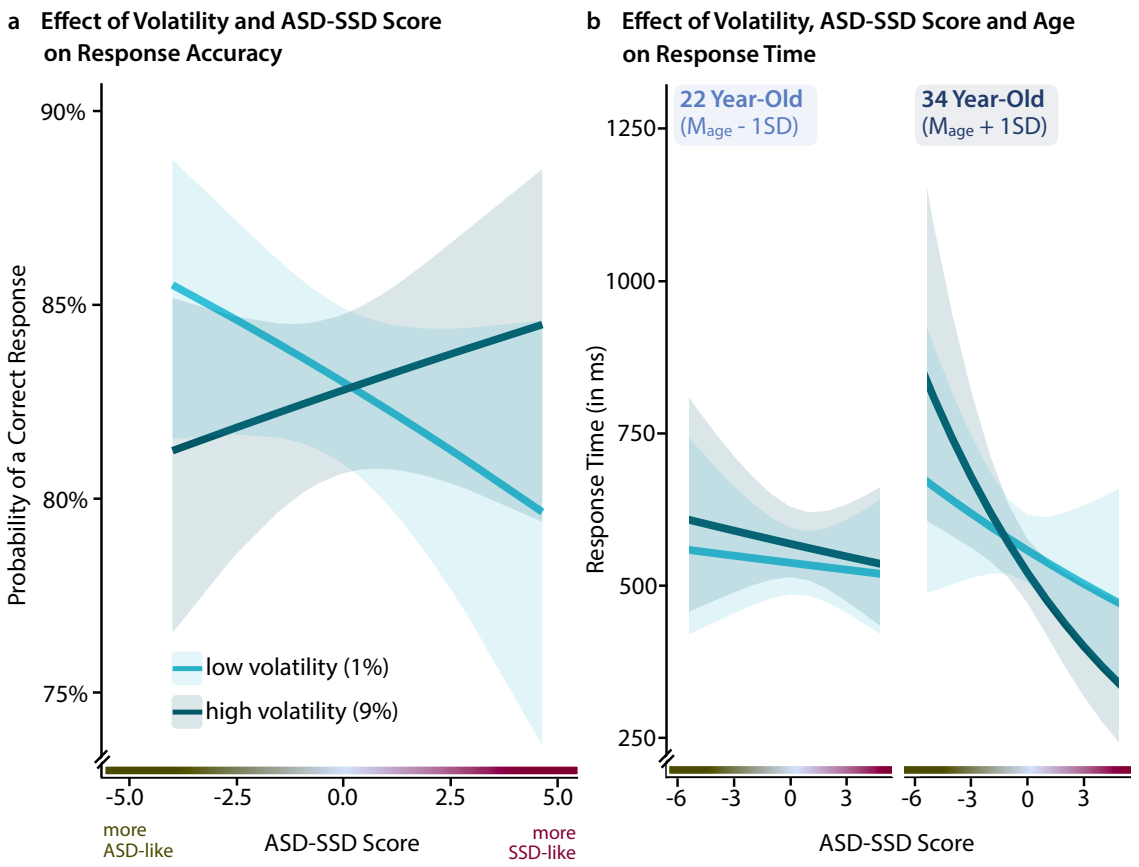

Figure 7. Effects of age, volatility and ASD-SSD score on response accuracy and response time in the auditory discrimination task. Individuals with more ASD-like profiles showed the greatest benefit from low volatility, evidenced by higher response accuracy (panel a) and faster response times (panel b) compared to high volatility. In contrast, individuals with more SSD-like profiles exhibited the opposite pattern, demonstrating improved performance under high-volatility conditions.

DISCUSSION

In the present study, we introduced a refined method for computing ASD-SSD scores, which retains the core outcomes of traditional scoring methods while improving psychometric robustness. We also examined how ASD-SSD scores vary as a function of demographic factors, most notably age, revealing a systematic shift in cognitive-perceptual style between younger and older participants. Finally, we demonstrated how these individual differences can be meaningfully integrated into predictive processing models, shedding light on the mechanisms underlying age-related cognitive change.

Toward a more robust model of the ASD-SSD continuum

To ensure greater psychometric precision in computing ASD-SSD scores, we applied an updated item-scoring scheme and factor structure for the AQ, drawing on more recent work that refined item weightings (Austin, 2005) and reorganised items into five

subscales as the original (Baron-Cohen et al., 2001), albeit with different item groupings (Kloosterman et al., 2011). In contrast, as the SPQ's scoring and subscale structure remain largely uncontested, we retained the original framework introduced by (Raine, 1991).

Compared to established methods (Dinsdale et al., 2013; Marsicano & Melcher, 2025; Tarasi, Borgomaneri, et al., 2023; Tarasi, Martelli, et al., 2023), the revised model for computing ASD-SSD scores produces highly similar score distributions while benefiting from a stronger theoretical and statistical foundation (English et al., 2020). This makes it better suited for capturing inter-individual differences in non-clinical populations.

Effects of questionnaire gender biases on ASD-SSD scores

Results revealed ASD-SSD scores were lower in self-identified men compared to women, which most likely arises from well-documented gender biases in the AQ and SPQ.

In the AQ, men typically score higher than women in non-clinical samples (Baron-Cohen et al., 2001; Kunihira et al., 2006), partly because the questionnaire (in the original Baron-Cohen version) more readily captures male-typical manifestations of autistic. To be precise, men tend to score lower than women on AQ subscales social skill, attention switching, communication, and imagination, while there are no gender-differences between subscale scores of attention to detail (Kunihira et al., 2006; Pisula et al., 2013).

Evidence from the SPQ (1991) and the closely related *Wisconsin Schizotypy Scale* (Chapman et al., 1976, 1978; Eckblad & Chapman, 1983) suggests gender differences in schizotypal traits, with men tend to score lower than women on perceptual-cognitive subscales such as *Unusual Perceptual Experiences* and *Magical Thinking* and higher on social subscales such as *Social Anhedonia* and *Constricted Affect* (Miettunen & Jääskeläinen, 2010; Raine, 1992). Within our ASD-SSD framework, perceptual-cognitive subscales load in the opposite direction to autistic traits, while social subscales load in the same direction. This means that men's response patterns align more closely with an ASD-like cognitive-perceptual style, resulting in lower overall ASD-SSD scores. However, this pattern likely reflects, at least in part, gender-related measurement bias in the questionnaires rather than true differences in underlying traits.

Taken together, the observed gender effect may thus reflect a combination of genuine gender differences in trait expression and systematic bias in the instruments used to capture them.

Association of age and cognitive-perceptual style

While our cross-sectional design limits the ability to draw causal conclusions, the observed association between age and cognitive-perceptual style offers a compelling starting point for interpreting potential shifts in perceptual processing across the adult lifespan. Specifically, older adults appear to rely more heavily on sensory evidence than on prior expectations – an initially counterintuitive finding given the dual facts of age-related sensory decline and the accumulation of life experience from which predictive priors could, in theory, be drawn. As such, this pattern is difficult to reconcile with the idea that priors can serve as a compensatory mechanism when sensory input becomes less reliable. If perceptual inference were adaptively tuned, one might expect older individuals to increase their reliance on prior knowledge to counteract noisy or degraded input. Instead, our data support the opposite conclusion.

To understand this shift, it is essential to examine age-related changes at the subscale level: Do older individuals develop stronger ASD-like traits, or is the movement towards the autistic end of the ASD-SSD continuum primarily driven by a reduction in SSD-like symptoms?

In an exploratory analysis on the relationship between increasing age and individual AQ and SPQ subscale scores, we found that age was related to a decline in symptom severity on the subscales *Ideas of Reference*, *Social Anxiety*, *Unusual Perceptual Experiences*, and *Repetitive or Restricted Behaviour* – all subscales that mirror how individuals react to ambiguous, potentially threatening, or distressing situations or stimuli. Hence, this pattern may suggest that older individuals experience fewer intense reactions to such stimuli. Indeed, with increasing age, adults often become more emotionally regulated and more inclined to interpret ambiguous stimuli in a positive way (Isaacowitz, 2022; Burr et al., 2021; Carstensen et al., 2011; Barber et al., 2022; Juang and Knight, 2016; Rodgers et al., 2012; Trapp et al., 2022).

However, this apparent reduction in reactive symptoms does not necessarily imply clinical improvement. In fact, increasing age was positively associated with higher scores on subscales such as *Odd Beliefs or Magical Thinking*, (poor) *Imagination*, and (poor) *Social Skills*, with the decline in social skills exerting an especially heavy influence on ASD-SSD scores. This indicates that while emotional or perceptual reactivity may decline, more trait-like cognitive-perceptual impairments – and their impact on social functioning – may actually increase with age.

In sum, our exploratory findings suggest that while cognitive-perceptual symptoms of ASD may persist or even intensify with age – particularly in the domain of social skills – subjective distress and sensitivity to perceived threats or ambiguous

stimuli on the SSD-side of the ASD-SSD continuum tend to diminish. This combination appears to be a key driver of the observed age-related shift towards the ASD end of the ASD-SSD continuum. As a consequence, to more accurately capture cognitive-perceptual style instead of changes in social cognition or coping mechanisms along this dimension, it may be advisable to entirely revise the computation of ASD-SSD scores by prioritising subscales that directly assess symptom severity (e.g. *Odd Beliefs / Magical Thinking*), and by excluding subscales that reflect responses to symptoms (e.g. *Repetitive / Restrictive Behaviours* or *Social Anxiety*) or aspects of social cognition not directly related to perceptual processing (e.g. *Social Skills*).

While the explanation above seems plausible, there are two alternative interpretations that may not be the primary drivers of the observed pattern but could nonetheless contribute to the age-related shift towards less SSD- and more ASD-like cognitive-perceptual processing.

First, one potential explanation for the observed shift is a *healthy survivor bias*, meaning the selective attrition of individuals scoring high on ASD-SSD (i.e. exhibiting more SSD-like cognition and perception) over time. In younger age groups, high SSD scores may capture individuals who are prodromal or at increased risk for developing schizophrenia-spectrum disorders, but who have not yet manifested clinically relevant symptoms. As these individuals transition into clinical categories, they are likely to be excluded from participation in non-clinical samples later in life—resulting in a downward shift in observed ASD-SSD scores among older adults. However, the lifetime prevalence of SSD remains relatively low (about 2.3 to 2.5%; Chang et al., 2017; Subramaniam et al., 2021), and the absence of extreme outliers in our data suggests it is unlikely that such a bias could meaningfully account for the observed age-related decline in ASD-SSD scores.

The second explanation for the observed age-related negative shift in ASD-SSD scores is a genuine developmental shift in the brain in early adulthood: While some studies suggest SSD symptom severity increases with age, there are some accounts of symptom severity in the positive and disorganised dimensions of schizotypy tending to decline in early adulthood due to increases in white matter integrity – particularly in tracts such as the cingulum and anterior thalamic radiation (Derome et al., 2025; Kochunov & Hong, 2014). In younger adults, such effects which may buffer or mask SSD-like traits. However, this cannot explain a shift towards more ASD-like processing over the adult lifespan we show in the present study.

To summarise, the mechanisms underlying age-related shifts in cognitive-perceptual style remain poorly understood and warrant further investigation – particularly given their potential relevance for developing tailored coping strategies in older adults with elevated SSD traits. This need is underscored by the limitations of our current cross-sectional design, which preclude any causal interpretation of the observed age effects. While a genuine age-related shift in cognitive-perceptual style appears plausible, the observed age effect in the present study may instead reflect generational differences rather than developmental change per se. Thus, longitudinal research will be essential to disentangle these possibilities and to clarify the mechanisms driving apparent changes in cognitive-perceptual style across the adult lifespan.

Moreover, the current approach to computing the ASD-SSD continuum may require further refinement, as it places disproportionate weight on social functioning and coping responses rather than on perceptual symptomatology itself. This may obscure genuine differences in perceptual processing tendencies across the adult lifespan.

Cognitive perceptual style shapes predictive processing in a language task

To demonstrate the validity of our revised approach to compute individual ASD-SSD scores as a measure of cognitive-perceptual style, we employed these scores to model both predictive processing in a self-paced reading task as well as the temporal dependencies of non-lexically driven response times in the same task.

As hypothesised, individuals read more slowly with increasing age, decreasing word predictability, and a more prior-driven, SSD-like cognitive-perceptual style. While age-related slowing and the modulating effect of word predictability on reading times are well-established phenomena (Chen et al., 2019; de Varda & Marelli, 2022; Liu et al., 2017; Lowder et al., 2018; Mitzner & Rogers, 2006; Monsalve et al., 2012; Shain et al., 2024), the third finding – that individuals with a more prior-driven, SSD-like processing style read more slowly than those with a more stimulus-driven, ASD-like style – warrants further consideration.

To unpack this pattern, we examined the interaction between cognitive-perceptual style and word predictability. Results revealed that participants with a more stimulus-driven, ASD-like processing style showed stronger effects of word predictability on reading time. In other words, they read faster when words were highly predictable, whereas participants with a more prior-driven, SSD-like processing style exhibited weaker predictability effects. Given that our materials were overall highly predictable (due to the low occurrence of unpredictable words), this differential benefit

from predictability may explain the group difference in mean reading speed. That is, the observed slowing in prior-driven individuals may not reflect a general cognitive inefficiency, but a reduced sensitivity to word-level lexical changes in the reading material. This interpretation suggests that individual differences in predictive processing style influence not only how word predictability modulates reading, but also overall reading speed under high-predictability conditions.

Further, we found that age modulated the effect of word surprisal with older participants exhibiting stronger predictability effects. We interpret this as a compensatory mechanism: with advancing age, individuals may increasingly rely on predictive processing to offset cognitive and sensory decline (see Schuckart et al. (2024) for a more detailed discussion).

This age-related amplification of predictability effects also modulated the interaction between word predictability and cognitive-perceptual style. Specifically, the strongest word predictability effects were observed in older adults with a more sensory-driven, ASD-like processing style. In contrast, while predictability effects were also amplified in older individuals with a more prior-driven, SSD-like style compared to their younger counterparts, they remained weaker than in age-matched peers with a more sensory-driven processing style.

The literature converges on the notion that word predictability effects are complex – facilitating processing when predictions are confirmed, yet sometimes imposing costs when predictions are violated (Ryskin & Nieuwland, 2023; Shain et al., 2024; Staub, 2025; Van Petten & Luka, 2012; Wong et al., 2024, 2025). Our present sample included participants with pronounced variability in predictive processing, enabling a closer examination of these individual differences and offering new insights into the ongoing debate surrounding the potential costs of predictive processing.

Specifically, individuals with a more sensory-driven, ASD-like processing style exhibited longer reading times for low-predictability words and shorter reading times for high-predictability words than their age-matched peers with a more prior-driven, SSD-like style. This pattern suggests that predictive processing facilitates reading when expectations are met – as is typically the case for high-predictability words – but slows it down when predictions fail and prediction errors must be integrated, which is more likely for low-predictability words.

Given that naturalistic texts typically contain a large proportion of highly predictable function words such as articles, prepositions, conjunctions or pronouns (Bell et al., 2009), predictive processing should, on average, confer a processing advantage – despite occasional costs when predictions are violated. This implies

increased reliance on prediction with advancing age may serve as an adaptive strategy to maintain reading fluency in the face of sensory and executive decline, further supporting our previous findings (2024).

Beyond predicting reading times from lexical and cognitive-perceptual factors like ASD-SSD, we explored whether non-lexically driven response dynamics – captured by autocorrelations in residualised reading times – also relate to individual differences. Residualising removed effects of lexical, task, and age influences, isolating intrinsic temporal patterns in reading behaviour. As expected, we identified two distinct autocorrelation profiles reflecting both steady and variable reading patterns across participants. However, contrary to our initial hypothesis, these patterns did not correlate with ASD-SSD scores. This dissociation reveals that while ASD-SSD robustly predicts how individuals process linguistic information, it does not account for more general fluctuations in response stability or temporal structure. Instead, these autocorrelation patterns likely index independent factors such as executive control, arousal, motor organisation or cognitive abilities (Duschek et al., 2022; Junghaenel et al., 2022; Karalunas et al., 2014; Vasquez et al., 2018). Crucially, this uncovers autocorrelation structure as a novel behavioural marker capturing meaningful individual variability orthogonal to age, lexical effects, or cognitive-perceptual style – opening promising avenues for future research into cognitive dynamics beyond the ASD-SSD framework.

Cognitive-perceptual style and volatility

Beyond the well-documented differences in sensory and executive capacities between older and younger adults (Idowu & Szameitat, 2023; Salthouse et al., 2003; Verhaeghen et al., 2003), it is worth considering whether older adults perceive their environment as inherently less volatile (i.e., prone to sudden changes) than younger adults do. This might either be the case because they had more time accumulating experiences on how volatile stimuli in daily life really tend to be, or because they actively seek out less volatile environments that align with their preferences and cognitive capacities. For instance, younger adults might gravitate toward highly dynamic environments and experiences because they find them engaging and stimulating (e.g., loud night clubs, watching fast-paced video reels, consuming multiple types of media at the same time) while older adults may prefer less volatile environments that are more stable and thus less overwhelming – both to match their sensory capacities and to reduce cognitive load. Such self-selected environments might reinforce age-related differences in perceived volatility, creating a cycle where preferences and experiences further diverge with age.

Motivated by these considerations, in the present study we asked whether individual differences in cognitive-perceptual style correspond to a predilection for environments defined by either low volatility – stable and predictable – or high volatility – rapidly shifting and stimulating.

Results from an exploratory analysis (N = 28, age: 21–41 years) offer tentative empirical support for this idea. In an auditory discrimination task, participants judged whether a voice or non-voice sound was presented on each trial, under varying levels of volatility. Our results suggest that volatility interacts with individual cognitive-perceptual style to shape perceptual outcomes: Participants scoring high on the ASD-SSD continuum (i.e., exhibiting more SSD-like processing) showed faster response times and higher accuracy under high-volatility conditions, whereas the opposite pattern emerged for individuals with more ASD-like profiles. These findings suggest that optimal performance depends on the interplay between cognitive-perceptual style and environmental volatility, potentially influencing individuals' preferences for different levels of environmental stability.

Given that older individuals in our main sample (N = 340, age range 18–82 years) tended to exhibit more sensory-driven, ASD-like processing, understanding the interplay between age, cognitive-perceptual style, and environmental volatility is crucial for designing inclusive environments. Whether in digital platforms, workplaces, housing, clinical settings, or public spaces, recognizing how these factors influence the perception of volatility and environmental preferences enables us to create spaces that better accommodate the diverse needs and capacities of all individuals.

Conclusion

Our findings establish the ASD-SSD continuum as a meaningful axis of cognitive-perceptual variability that interacts with age to shape predictive processing in language comprehension. This challenges one-size-fits-all accounts of prediction and underscores the importance of lifespan-sensitive, individualised frameworks in the study of predictive perceptual processing.

MATERIALS & METHODS

Participants

For the current analysis, we pooled questionnaire data from six studies where participants were asked to complete the Autism Spectrum Quotient (AQ; Baron-Cohen et al., 2001) and the Schizotypal Personality Questionnaire (SPQ; Raine, 1991). The pooled sample comprised 393 native German participants aged 18 to 82 years (M = 38.40 ± 16.78 years) with a balanced gender distribution of 53.69% male and 40.20% female participants.

Participants completed the questionnaires in digital format either online (N = 233) or in a controlled lab session (N = 127), while a smaller subset (N = 33) completed them in pen-and-paper format at home. Those tested in the lab were informed that the experimenter could not view their responses. Remote participants were assured that their data would be stored under an anonymous ID, making it impossible to link responses to individuals.

Recruitment methods varied across studies: Participants were either enlisted via convenience sampling, primarily through personal networks, recruited through the online platform Prolific, or the participant databases of the University of Lübeck and the Max Planck Institute in Leipzig. All participants were native German speakers with no history of psychiatric or neurological disorders or substance abuse. Individuals who had consumed drugs or alcohol immediately prior to the measurement were not eligible for participation in the respective study and were therefore not included in this sample.

Some analyses were conducted on subsamples of the full dataset, depending on data availability and task completion. To compute the factor loadings used to derive ASD-SSD scores, we employed the full sample of 393 participants.

For examining the effects of age, education, and gender on ASD-SSD scores, we included all participants with complete information on these variables. We excluded individuals with missing data and those reporting implausibly low education values (e.g., three or four years of schooling, which is not possible within the German education system). This resulted in a subsample of N = 340 participants aged 18 to 82 years (M = 38.94 ± 17.11 years; 59.12% female), with a mean of 14.21 ± 2.41 years of schooling. This value is slightly lower than the German average of 14.3 years reported in 2023 (United Nations Development Programme, 2025), likely due to our inclusion of participants aged 18–25 who may not yet have completed their education; the UNDP report includes only individuals aged 25 and above.

For investigating the relationship of individual scores on the ASD-SSD continuum with behavioural markers of predictive processing, we employed a sub-sample of N = 247 participants aged 18 to 82 years (M = 42.78 ± 17.35 years; 55.87% female) who had performed a self-paced reading task in addition to completing the questionnaires.

Finally, to explore how cognitive-perceptual style might interact with volatility, we analysed data of another subsample comprising N = 28 healthy participants aged 21–41 years (M = 28.14, SD = 5.91), with a balanced gender distribution (50% female) who completed both the questionnaires and an auditory detection task in which volatility was systematically varied.

Ethics Statement

In all studies, participation was contingent upon providing written informed consent. Participants were compensated either financially (€12/h) or with course credits. All studies were conducted in accordance with the Declaration of Helsinki and were approved by the local ethics committees of the University of Lübeck and Leipzig University.

ASD-SSD Scores

Derivation of Individual ASD-SSD scores

In all six studies, participants were asked to complete both the 50-item version of the AQ (Baron-Cohen et al., 2001) and the 74-item version of the SPQ (Raine, 1991), to assess subclinical autistic and schizotypal traits, respectively.

The SPQ uses a binary answer format, with all questions being endorsed "yes" scoring one point. They are all phrased in the same direction, such that a "yes" response consistently indicates more SSD-like cognition, perception, or behaviour; therefore, no reverse-keying is required. Items were scored and aggregated into the nine original subscales – *Ideas of Reference* (IR), Excessive Social Anxiety (SA), *Odd Beliefs or Magical Thinking* (OB), *Unusual Perceptual Experiences* (UPE), *Odd or Eccentric Behaviour* (OBH), *No Close Friends* (NCF), *Odd Speech* (OS), *Constricted Affect* (CA) and *Suspiciousness* (SUS) – following the original framework proposed by (Raine, 1991). The specific items constituting each subscale are listed in the supplementary materials (see Table S2).

For the AQ, subscale scores were derived using three different methods: First, we applied the five original subscales proposed by Baron Cohen et al. (2001) and used

in the studies by Tarasi et al. (Tarasi, Borgomaneri, et al., 2023; Tarasi, di Pellegrino, et al., 2022; Tarasi, Martelli, et al., 2023; Tarasi, Trajkovic, et al., 2022), which reflect poor *Social Skills* (SS), *Attention-Switching* (AS), *Communication Skills* (CS), and *Imagination* (I) as well as exceptional *Attention to Detail* (AD). In the AQ, we applied the classical scoring method in which the 4-point Likert scale is collapsed into a binary format: responses indicating either mild or strong endorsement of ASD-like behaviour, perception, or cognition are scored as 1, and all others as 0. This approach reflects the traditional scoring procedure (Baron-Cohen et al., 2001), despite the underlying Likert response format.

Second, we also computed AQ subscale scores using two more recent, alternative factor models as suggested by English et al. (2020): the three-subscale system by Russel-Smith et al. (2011), which includes the subscales *Social Skills* (SS), *Details/Patterns* (DP), and *Communication/Mindreading* (CM); and the five-subscale system by Kloosterman et al. (2011), comprising Social Skills (SS), Communication/Mindreading (CM), Restricted/Repetitive Behaviour (RRB), Imagination (I) and Attention to Detail (AD). A complete item-to-subscale mapping is provided in the supplementary materials (see Table S2).

Prior to further analyses, we assessed the factorability of the correlation matrices underlying combinations of SPQ subscale scores with AQ subscale score derived from three different factor models: Baron-Cohen, Russell-Smith, and Kloosterman. For this purpose, we computed the *Kaiser-Meyer-Olkin Measure of Sampling Adequacy* (KMO-MSA; Kaiser, 1974) as well as *Bartlett's Test of Sphericity* (Bartlett, 1937).

As KMO-MSA results indicated acceptable factorability only for the Baron-Cohen and Kloosterman models, we limited subsequent analyses to comparisons based on the Baron-Cohen- and Kloosterman-based AQ subscales and their corresponding ASD-SSD scores.

Following these factorability checks, we conducted two *Principal Component Analyses* (PCA) to derive loadings for weighting AQ and SPQ subscales in the computation of individual ASD-SSD scores. One PCA included all SPQ subscales along with the Baron-Cohen–based AQ subscales; the other combined SPQ subscales with the Kloosterman-based AQ subscales. In line with previous studies deriving individual ASD-SSD scores using PCA, and following the recommendation of Luca Tarasi (personal communication, December 13, 2024), we used unrotated PCAs in the present analyses.

When PCA is applied to AQ and SPQ subscale scores, it typically reveals two orthogonal components: While the first Principal Component (PC1) captures commonalities between the cognitive-perceptive styles of ASD and SSD, the loadings

of the second Principal Component (PC2) distinguish between autistic-like and positive schizotypal traits (Del Giudice et al., 2014; Dinsdale et al., 2013; Tarasi, Borgomaneri, et al., 2023; Tarasi, Martelli, et al., 2023). Accordingly, we extracted loadings from PC2 to compute individual ASD-SSD scores.

It is important to note that our reported loadings show a sign flip relative to those reported by (Tarasi, Martelli, et al., 2023). This is a known and purely arbitrary feature of PCA: As PCA is based on eigenvectors, the direction (sign) of a component is mathematically undefined – flipping all signs yields an equivalent solution (Jolliffe, 2002). As a result, the sign of each component can differ across samples or software implementations without affecting the underlying structure. However, to facilitate interpretability and ensure comparability across studies, we subsequently aligned the direction of PC2 with previous work by flipping all signs such that higher ASD-SSD scores reflect more SSD-like traits, and lower scores reflect more ASD-like traits.

Employing the extracted loadings of PC2 from two PCAs, and the previously published loadings from Tarasi et al. (2023), we computed individual ASD–SSD scores based on three distinct models, summarised in Table 1. Models 1 and 2 both use the SPQ item scoring and subscale structure from Raine (1991) as well as the item scoring and factor structure proposed by Baron-Cohen et al. (2001), differing only in the sample used to compute loadings (Tarasi's smaller, younger sample versus our larger, age-diverse sample). Model 3 applies the SPQ item scoring and factor structure from Raine et al. (1991), combined with the more nuanced AQ item scoring from Austin (2005) and the alternative, more psychometrically sound factor structure proposed by Kloosterman et al. (2011), also computed using questionnaire data from our larger sample. This approach enabled us to validate our revised method (model 3) against both the original method as implemented here (model 2) and a previously published model of the same structure as our model 2, known to yield robust results in a psychophysical task (model 1).

For each model, we first *z*-scored all AQ and SPQ subscale scores and then multiplied the resulting matrix by the respective PC2 loading vector. This yielded one ASD–SSD score per participant for each model, reflecting their position along the diametric axis defined by PC2. We ran Spearman rank correlations between the ASD–SSD scores from each model to assess the consistency of the scoring approaches.

As we observed strong correlations between established ASD–SSD scores (models 1 and 2) and the revised scores (model 3), all subsequent analyses employed ASD–SSD scores computed with the revised scoring method.

The PCA data analysis was carried out in *R* version 4.4.1 (R Core Team, 2023), using the packages *factoextra* (Kassambara & Mundt, 2016) and *psych (Revelle, 2025)*. Questionnaires were implemented in *lab.js* (Henninger et al., 2024) and either run locally or hosted on *OpenLab* (Shevchenko, 2022), with data being saved on *OSF* (Foster & Deardorff, 2017).

Statistical Analysis of ASD-SSD scores

To examine the potential influence of age, gender and education on individual cognitive-perceptual style, we fitted a linear model (LM) with ASD–SSD scores as the dependent variable, with age, gender, and education as predictors. Additionally, as some participants completed the questionnaires in a controlled lab environment in the presence of at least one experimenter, we accounted for potential social desirability bias by including a binary predictor ('presence of experimenter'). For this line of analyses, we employed a subsample of 340 participants. To assess the effect of education, missing values for years of education were approximated based on the minimum standard duration typically required to obtain the reported highest academic degree. This approximation did not account for individual variations such as skipping years or alternative educational trajectories. All continuous predictors were mean-centred prior to analysis. The full model formula was:

ASD-SSD score ~ presence of experimenter + age + education + gender

To further assess the robustness of our effects, we employed 5-fold cross-validation (Poldrack et al., 2020). Specifically, we divided the full sample of 340 participants into five folds of 68 participants, stratified by gender. The resulting folds – and the original full sample – were highly comparable in their distributions of gender, age, and education (see Figure 4c). This ensured that each fold provided a balanced representation across the key demographic variables and adequately covered the full range of combinations of age, education, and gender.

Self-paced Reading Task

Experimental Design

A subsample of 247 participants completed a self-paced reading task prior to questionnaire completion (see Fig. 3a). In this task, participants read short newspaper articles (300 words each) word-by-word at their own pace, advancing through the text

by pressing the space bar. Following each article, they answered three multiple-choice comprehension questions. To manipulate cognitive load, some blocks included an orthogonal n-back task based on the font colour of the words, which participants practiced separately at the start of the experiment (see Schuckart et al. (2024) for further details on the task).

While all participants completed both the *Reading Only* (self-paced reading without the n-back) and *Dual Task* blocks (reading combined with the n-back), the present analysis focuses exclusively on the *Reading Only* condition to characterize baseline reading behaviour without cognitive load interference.

Following our previous study (Schuckart et al., 2024), we used word-level reading times alongside comprehension accuracy calculated at both the participant and block levels as the percentage of correctly answered questions. Furthermore, we derived a mean d-prime score for each participant, indexing working memory capacity, from the non-verbal single-task n-back training blocks.

As data were pooled from three related experiments, minor procedural variations existed: participants completed either two or three Reading Only blocks (N = 185, sub-sample from Schuckart et al. [2024]; and N = 62 from a new sample, respectively), resulting in some participants contributing more data than others. Texts were selected from a pool of ten, meaning text selection varied across participants.

Two of the studies used *lab.js* (Henninger et al., 2024) for implementation, with experiments run either locally in a controlled lab setting or online via *OpenLab* and *OSF* for hosting and data storage (Foster & Deardorff, 2017; Shevchenko, 2022). The third study employed Python with the *PsychoPy* package (Peirce et al., 2019) and was run locally in a controlled lab setting.

Generation of Word Surprisal and Entropy Scores

For all texts presented in the reading task, we computed word-level entropy and surprisal. Word entropy reflects the uncertainty about which word will come next before it is encountered – that is, the unpredictability inherent in the prediction itself. Word surprisal, in contrast, quantifies how unexpected a word is given its preceding context, with higher values indicating greater unpredictability and processing difficulty upon encountering the word. Thus, both measures capture aspects of word predictability: entropy indexes pre-stimulus uncertainty, while surprisal indexes post-stimulus processing difficulty.

Preprocessing and Statistical Analysis of Reading Times

To examine how individual cognitive-perceptual style relates to participants' perceptual processing, we conducted two complementary analyses on the reading time data – one targeting *non-linguistic* perceptual processing, and the other focusing on *linguistic* perceptual processing.

For the first line of analyses, which investigated the effects of age and cognitive-perceptual style on linguistic processing, we employed two linear mixed-effects models (LMMs) to assess the influence of age, individual ASD-SSD scores, and lexical predictors – such as word surprisal and entropy – on unresidualised reading times, thereby focusing on linguistic perceptual processing.

For the second line of analyses on the effects of age and different cognitive-perceptual styles on non-linguistic processing, we computed autocorrelations of residualised reading times and identified clusters of temporal patterns, which we subsequently examined in relation to participants' ASD-SSD scores. By residualising reading times before computing autocorrelations, we effectively removed lexical influences, isolating non-linguistic perceptual processing such as general perceptual or attentional fluctuations during the reading task.

The following section provides a detailed description of each analysis pipeline, outlining the preprocessing steps and statistical approaches employed to investigate non-linguistic and linguistic perceptual processing, respectively.

For the first line of analyses, we excluded all blocks in which participants appeared not to comprehend the reading material. Subsequently, we removed outlier trials based on reading times that were either excessively short or long. Specifically, we first excluded pauses of 5000 ms or longer to remove extended breaks, which affected 0.8% of trials. We then applied a POMS transformation (Little, 2013) to the reading times, followed by a *z*-transformation of the square-root–transformed values to identify and exclude statistical outliers (Berger & Kiefer, 2021; Cousineau & Chartier, 2010). On average, 2.05% of trials were excluded, with 72.724 ± 11.665 excluded trials per participant. After outlier exclusion, the subsequent analysis was conducted on the raw reading times, which were log-transformed to account for skewness in their distribution.

To assess the joint influence of age, cognitive-perceptual style, and word surprisal on language processing on single-word level, we fitted a linear mixed-effects model (LMM) on log-transformed reading times. Its structure closely followed that of our previous study (Schuckart et al., 2024), incorporating the following continuous fixed effects: word frequency (as estimated using Python's *wordfreq* package; Speer et al.,

2018), word length, and entropy as lexical measures; comprehension accuracy at the block and participant level as task performance measures; mean d-prime from a non-linguistic n-back task as a proxy for individual working memory capacity; log-transformed reading time from the previous word to account for potential sequential modulation effects if the previous trial was ended prematurely or the participant paused reading within a block; and finally block and trial number to control for training and fatigue effects. Recording location (lab vs. online) was included as a categorical control variable to account for potential differences in task engagement or familiarity with the used equipment. Additionally, similar to the original model used in our previous study (Schuckart et al., 2024), we added age and word surprisal as continuous predictors to the model, alongside each participant's individual ASD-SSD score, as well as their two- and three-way interactions. Random effects included random intercepts for participants as well as the effect of text and the current word. All continuous predictors were centred.

log(RT) ~ RT of previous word +
mean d-prime from single tasks +
mean comprehension question performance +
block-level deviation from mean comprehension question performance +
recording location + word entropy +
word frequency + word length (without punctuation) +
block number + trial number +
surprisal * age * ASD-SSD score +
(1 | ID) + (1 | text number) + (1 | word)

Note. Model structure. RT = Reading Time, ID = participant.

For the second line of analyses, we excluded blocks in which participants failed to answer at least one of three multiple-choice comprehension questions correctly, based on the assumption that such blocks were not read attentively or meaningfully engaged with. In contrast to the first line of analyses, we retained the raw reading times without excluding outlier trials, as computing block-wise autocorrelations relies on the continuity of the full series of reading times.

We then fitted a linear mixed-effects model (LMM) predicting log-transformed reading times from demographical factors, a set of lexical and experimental variables, as well as task performance measures. Demographical factors included age as well as participant-wise mean d-primes from two non-lexical n-back task blocks as a proxy of

each participant's working memory capacity. Experimental factors comprised block number, trial number, and recording location (lab vs. online); task performance was indexed by comprehension question accuracy. Lexical predictors were word frequency, word length, word entropy, and word surprisal. Since excluding individual trials was not an option, as for the subsequent autocorrelation analysis it was crucial to preserve the integrity of each block's structure, we included an additional binary predictor indicating trials that would have otherwise been excluded as outliers. Finally, we also included an interaction term for the effect of age and word surprisal.

Random effects included random intercepts for participants as well as the effects of text choice and the current word. All continuous predictors were centred.

```
log(RT) ~ outlier trial +
        mean comprehension question performance +
        block-level deviation from mean comprehension question performance +
        recording location +
        word frequency + word length (without punctuation) + word entropy +
        block number + trial number +
        mean d-prime from n-back tasks +
        word surprisal * age +
        (1 | ID) + (1 | text number) + (1 | word)
```

Note. Model structure. RT = Reading Time, ID = participant.

From this model, we extracted residualised reading times – that is, the variance in reading times unexplained by the lexical, demographic, experimental and task performance predictors – leaving individual cognitive-perceptual style and perceptual processes not explained by the selected predictor variables as the primary sources of variation for subsequent analyses.

For each participant, we then calculated the autocorrelation of the residualised reading times separately for the individual Reading Only blocks, across lags ranging from 0 to 100 words (i.e., from the current word at index n up to the 100th preceding word at index n-100). Each block consisted of 300 words, ensuring sufficient length for estimating longer-range dependencies. From each resulting autocorrelation sequence, we excluded the first value, as the correlation of each word's reading time with itself is trivially equal to 1. We limited our analysis to the first 30 lags, as (a) we did not expect

long-range autocorrelations during reading, and (b) estimates for higher lags were noisier due to reduced data availability.

Visual inspection of the resulting autocorrelation curves revealed two distinct temporal patterns. The first identified pattern showed a canonical decaying autocorrelation pattern, reflecting stronger temporal dependencies and relatively consistent pacing during the reading task. The second pattern was characterised by elevated autocorrelations at short lags, and relatively low, flat autocorrelations at longer lags, indicative of high inter-trial variability and minimal temporal dependency between successive reading times.

For subsequent analyses, we averaged autocorrelations across blocks to reduce noise and derive a single autocorrelation function per participant. Following this, to formally identify and investigate the observed patterns, we first conducted a Principal Component Analysis (PCA) across participants and lags to identify latent structures in the autocorrelations. Following this, we applied k-means clustering to the participant scores on the first two principal components, as these captured the majority of variance (PC1: 12.9% explained variance; PC2: 7.6 %) and appeared to reflect two distinct groups in the PCA space (see Fig. 6a). The number of clusters was set to two, in line with the patterns uncovered by the PCA and our hypothesis that temporal autocorrelation profiles would separate into two distinct processing styles. The clustering was run with 25 random initializations to increase stability and minimise sensitivity to starting values. Participants were assigned to clusters based on Euclidean distance in the PCA space, resulting in two groups with distinct autocorrelation patterns (see Fig. 6b).

Subsequently, we fitted a linear model predicting ASD-SSD scores from autocorrelation cluster membership, with one cluster label assigned per participant. This allowed us to directly contrast the cognitive-perceptual profiles associated with structured versus disorganised temporal dynamics in reading behaviour.

The experiment was implemented in *lab.js* (Henninger et al., 2024), and either hosted online on *OpenLab* (Shevchenko, 2022) with data being saved on *OSF* (Foster & Deardorff, 2017), or run locally as controlled lab experiments. All data analyses were performed in *R* (version 4.4.1; R Core Team, 2023) using R's packages *dtwclust* (Sardá-Espinosa, 2024), *lme4* (Bates et al., 2015), *lmerTest* (Kuznetsova et al., 2017) and *sjPlot* (Lüdecke, 2024)).

Auditory Volatility Task

Experimental Design

To validate the ASD–SSD score as a marker of perceptual inference style, we re-analysed data from a separate laboratory study (N = 28) that employed a volatility-manipulated auditory discrimination task adapted from Erb et al. (2020).

In the task, participants were presented with sounds consisting of a 500 ms snippet of either a voice or a non-voice sound, embedded in 1000 ms of background noise, with the noise's frequency spectrum matched to that of the stimuli. In each trial, sensory uncertainty was modulated by randomly assigning one of five signal-to-noise ratio (SNR) levels (−10, −12, −14, −16 or −18 dB), with each negative value denoting the degree to which the acoustic stimulus was attenuated relative to the background noise. After each sound, participants were tasked to indicate via key press whether the presented sound contained a voice or a non-voice within a 2-second response window and received feedback on the accuracy of their response immediately afterward (see Fig. 3b). At the start of the experiment, participants completed a brief training block of 25 trials to familiarize themselves with this task.

Human voice sounds were non-verbal vocalisations corresponding to different emotions such as anger, fear or surprise, taken from the Montreal Affective Voices Database (Belin et al., 2008). Non-voice were taken from the Dataset for Environmental Sound Classification (Piczak, 2015) and comprised 66 different sound files containing non-human sounds from the categories animal sounds, natural soundscapes, domestic sounds, and urban noises.

At the onset of the experiment, participants were informed that the experiment would contain trial sequences consisting predominantly of either human voices or non-voice sounds (20% voices vs. 80% non-voices, or vice versa). However, they were not informed about the *volatility* – that is, when or how frequently the sequences favouring voices or non-voices would shift.

At its core, the experiment consisted of six blocks of 100 trials each, with two blocks assigned to each of three volatility conditions: low volatility (1% chance of sequence change after each trial, resulting in stable and predictable stimulus sequences), medium volatility (3% change probability), and high volatility (9% change probability). As changes in volatility were not cued, participants were required to infer the latent state of the environment over time.

The order of these three conditions within each experiment was randomised. The training block contained only one high-volatility sequence.

We recorded response times measured from stimulus offset, alongside trial-by-trial response accuracies indicating whether each response was correct. In addition to the auditory task, participants completed both AQ (Baron-Cohen et al., 2001) and SPQ (Raine, 1991).

Preprocessing and Statistical Analysis of Task Performance Measures

To investigate how cognitive-perceptual style, age, and task volatility influence performance in the auditory volatility experiment, we fitted two models – one linear mixed-effects model (LMM) on trial-level response times and one generalized linear mixed-effects model (GLMM) on trial-level response accuracy.

For the first model, trial-level response times were first cleaned by excluding all trials in which participants failed to respond within the 2-second window or exhibited responses under 200 ms. The remaining response times were then log-transformed to improve distributional properties and subsequently modeled using a linear mixed-effects framework. Fixed effects encompassed individual ASD-SSD scores, volatility condition (high vs. low), age, and their two- and three-way interactions. To account for potential confounding influences – including variability in noise levels, stimulus category (voice vs. non-voice), and temporal factors such as fatigue or learning over the course of the experiment – stimulus category, trial number, and noise level were incorporated as additional fixed effects. Random intercepts for participants accommodated individual differences, and all continuous predictors were mean-centred to facilitate interpretation.

log(RT) ~ **ASD-SSD score * volatility * age** +
stimulus category + trial number + noise level +
(1 | ID)

Note. Model structure. RT = Response Time, ID = participant.

For the second model on response accuracy, we employed a GLMM with a binomial (logistic) link function to model trial level hits and misses (i.e., response accuracy) in the auditory choice task.

The GLMM contained fixed effects for individual ASD-SSD scores, volatility (high vs. low) and age as well as their respective 2-way and 3-way interactions. Additionally, we added the stimulus category (voice vs. non-voice) as well as the noise level as nuisance regressors, and participant-level random intercepts. Again, all continuous predictors were mean-centred.

Response Accuracy ~ **ASD-SSD score * volatility * age** +
stimulus category + noise level +
(1 | ID)

Note. Model structure. ID = participant.

Acknowledgements

We thank Luca Tarasi for his generous advice on computing ASD-SSD scores and for kindly sharing his data with us; Sandra Martin for her assistance in collecting additional AQ and SPQ data for a subsample of our dataset; and Antonia Glagowski for kindly sharing her volatility experiment data with us.

Funding

This work was supported by German Research Foundation (DFG, OB 352/2-2 to JO).

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used GPT-4o-mini (OpenAI, Inc.) to rephrase sentences. The authors reviewed and edited any AI-generated content as needed and take full responsibility for the content of the publication.

Author Contributions

M.S.: conceptualization, data curation, formal analysis, investigation, methodology, project administration, visualisation, writing: original draft, review & editing

S.T.: formal analysis, methodology, writing: review & editing

S.M.: data curation, methodology

G.H.: methodology, funding acquisition, supervision

J.O.: conceptualization, formal analysis, methodology, funding acquisition, supervision, writing: review & editing

Competing Interest Statement

The authors declare that they have no competing interests.

Data Availability

All experimental and analysis scripts will be publicly accessible via the project's GitHub repository upon publication. Likewise, preprocessed data, model outputs, results, and model comparisons will be made available on OSF.

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