Neural signatures of impaired semantic contextualization in Autism Spectrum Disorder

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Competing interests

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ABSTRACT

Social and communicative deficits are defining characteristics of Autism Spectrum disorder (ASD). Some theories suggest that these challenges, among other autistic traits, may arise from differences in predictive coding, or how the brain uses context to predict and interpret incoming information. This idea has the potential to link symptoms of autism to specific neurocomputational processes, and is especially promising for communication, whose impairment is a hallmark of ASD. Here we leveraged the ability of large language models (LLMs) to quantify semantic contextualization to analyze a unique dataset of responses from hippocampal neurons obtained during language listening in three mild-to-severe autistic patients with comorbid epilepsy. Key elements of semantic coding were preserved in all three patients: single-neuron response dynamics, representation of word-word semantic relationships, and patterns of context-dependent shifts in meaning. However, relative to controls, ASD resulted in reduced neural signatures of contextualization: (1) neuronal responses were aligned with earlier, less contextual layers of GPT-2, (2) ASD patients had lower effective dimensionality of the neural subspace predicting semantics, (3) neural representations of word meaning were less influenced by preceding context, and (4) neural signatures of lexical surprisal were reduced. Together, these results support theories of autism that emphasize impairments in contextualization, and highlight the power of LLMs as a tool for quantifying the computational basis of neurodevelopmental disorders.

INTRODUCTION

Autism spectrum disorder (ASD) is characterized by differences in social communication, language use, and repetitive behavior, yet the neural mechanisms that give rise to these features remain incompletely understood (APA, 2013; Wachtel et al., 2024; Lord et al., 2018; Vogindroukas et al., 2022). A growing body of theory proposes that many autistic traits can be explained by altered predictive processing - differences in how the brain uses prior knowledge to anticipate incoming sensory and cognitive information (Pellicano and Burr 2012; Van de Cruys et al., 2014; Noel and Angelaki 2023; Lawson et al., 2014; Friston 2010; Chrysaitis and Series, 2022). While differences in predictive processing in autism have been documented at behavioral and large-scale neural levels (EEG, fMRI, and MEG), much less is known about how these alterations are implemented within neural circuits and at the level of individual neurons, where predictions must ultimately be generated (Schneider and Blank, 2026; Pellicano and Burr, 2012; Noel et al., 2021; Lawson et al., 2017; Grisoni et al., 2019; Schneebeli et al., 2022; Alamia et al., 2026; Sapey-Triomphe et al., 2023; Brodski-Guerniero et al., 2018; Qela et al., 2025; Gonzalez-Gadea et al., 2015; van Laarhoven et al., 2020; Gomez et al., 2014). Additionally, the theory remains controversial, in large part due to limitations in our ability to rigorously test it (Chrysaitis and Series, 2022; Lawson et al., 2014; Van de Cruys et al., 2014; Brock 2012; Van Boxtel and Lu, 2013). Moreover, it remains unclear how to extend these ideas to communication, which is a defining feature of autism. Despite this, language provides a particularly powerful domain in which to examine these mechanisms: comprehension depends on *contextualization*, the continuous integration of prior linguistic and world knowledge to constrain interpretation of words and meanings. If predictive computations are atypical in autism, then the neural representations that support semantic processing may differ not only in strength but in their structure and context sensitivity.

Understanding these differences at the circuit level is therefore essential for linking computational theories of autism to the neural basis of language and meaning. Over the past decade, computational approaches have increasingly been applied to behavioral and neural data in the study of psychiatric disease, giving rise to the field of computational psychiatry (Montague et al., 2012; Wang & Krystal, 2014; Huys et al., 2016; Adams et al., 2016; Friston et al., 2014). By formalizing cognition in quantitative, model-based terms, this framework has enabled researchers to uncover subtle alterations in learning, inference, and decision processes that are often invisible to traditional summary statistics or categorical diagnostic comparisons (Adams et al., 2016). Such methods have been particularly powerful in revealing latent structure in high-dimensional datasets, allowing small but systematic differences in cognitive computation to be detected at both the behavioral and neural levels (Kriegeskorte and Douglas, 2018). We see a parallel opportunity in the study of language and semantic representation in the brain: large language models (LLMs) provide richly structured, high-dimensional embeddings that capture fine-grained relationships among words and concepts, quantifying the geometry of semantic space (Mikolov et al., 2013; Devlin et al., 2018; Radford et al., 2019). When paired with neural recordings, these models make it possible to ask whether the organization of semantic

representations differs across populations, not only in overall magnitude or selectivity, but in the structure of the representational space itself (Franch et al., 2025; Katlowitz et al., 2025; Zhu et al., 2026). In this sense, LLMs extend the logic of computational psychiatry into the domain of neurolinguistics: rather than testing for gross differences in activation, they enable the detection of systematic shifts in how linguistic information is encoded, generalized, and abstracted.

The hippocampus is well positioned to mediate these processes because it sits at the intersection of memory, context, and semantic knowledge (Eichenbaum 2017; Shohamy and Turk-Browne, 2013; Duff and Brown-Schmidt, 2012). Beyond its canonical role in episodic memory, converging evidence indicates that hippocampal circuits contribute to the representation of concepts and relational structure, supporting the binding of items to context and the flexible generalization of meaning across experiences (Vigano and Piazza, 2021; Schapiro et al., 2017; Whittington et al., 2020; Constantinescu et al., 2016). Neurophysiological recordings in humans and animals have shown that hippocampal neurons can encode abstract features, conceptual relationships, and task-relevant structure, while neuropsychological and imaging studies implicate the medial temporal lobe in aspects of language comprehension that depend on contextual integration and associative inference (Franch et al., 2025; Katlowitz et al., 2025; Zhu et al., 2026; Piai et al., 2016; Duff and Brown-Schmidt, 2012; Courellis et al., 2024; Kolibius et al., 2023; Karkowski et al., 2025; Quiroga et al., 2005; Binder et al., 2009; Dijksterhuis et al., 2024). Importantly, several lines of evidence suggest that hippocampal structure and function are atypical in autism, including differences in volume and connectivity (Aylward et al., 1999; Reinhardt et al., 2023; Bhamidimarri et al., 2026; Hashimoto et al., 2021;), altered activation during memory and social tasks (Banker et al., 2021; Dickstein et al., 2013; Gomez et al., 2014), and disruptions in relational learning (Minor et al., 2023; Hashimoto et al., 2021). Together, these findings raise the possibility that circuit-level differences in hippocampal computation could contribute to the distinctive profile of contextual and semantic processing observed in autism, motivating direct investigation of how meaning is represented within hippocampal neurons.

RESULTS

Hippocampal encoding of semantic and phonemic features in autism

Fourteen adult patients (seven males and seven females) undergoing neural monitoring for epilepsy listened to 27 minutes of English speech (three monologues taken from the Moth podcast, **Methods, Figure 1A and B**). Of these patients, three were autistic (2 males and 1 female). Clinical and cognitive assessment scores from all patients are summarized in **Extended Data Fig. 1**. ASD patient 1 (ASD1) was autistic without intellectual disability (IQ, verbal, and perceptual scores fell within the control range - 30th, 20th, and 30th percentile respectively; Wechsler Adult Intelligence Scale IV). ASD patient 2 (ASD2) was autistic with mild intellectual disability (although their IQ score of 62 fell within the control range, 20th percentile) and impaired verbal comprehension (VCI = 68, lower than all controls; Perceptual reasoning (PRI) fell within control range - 20th percentile; Wechsler Adult Intelligence Scale IV). ASD patient 3 (ASD3) had profound autism (nonverbal with severe Intellectual Disability; functioning level 12 months; Adaptive Behavior Composite score 30 - Vineland Adaptive Behavior Scale). ASD patients were 22, 19, and 34 years old, respectively. The remaining patients were allistic, and collectively constitute our control group. The control patients were matched for intractable epilepsy status and had an age range of 18-48 (mean 30).

The monologues consisted of a total of 4,128 words, of which 792 were unique. We collected responses of isolated single neurons in the hippocampus (HPC, n=385 neurons in the control cohort; n=91 in the ASD cohort, **Extended Data Fig. 2**). Note that due to the small sample size and the potential heterogeneity, for this study all analyses are performed at the individual patient level. The number of neurons per patient in the control group ranged from 11-54; the number of recorded neurons in ASD patients was 51, 19, and 21, respectively. We aligned single neuron responses to word onsets. Neurons in both patient groups showed a characteristic ramping to a peak followed by a gradual decline in firing, although there was a great deal of diversity across neurons (**Figure 1C**). We computed firing rate during an epoch starting 80 ms after the onset of each word (to account for the approximate response latency) and lasting the duration of the word (see **Methods** and Franch et al., 2025). All firing rates were normalized by word duration.

Overall, evoked firing rates in the hippocampus of autistic patients 2 and 3 were modestly enhanced, relative to our control cohort, while firing rates in ASD1 were comparable to controls ($p = 0.31$, 0.0005, and 0.004 for ASD patients 1-3 respectively, Monte Carlo subsampling test; see **Methods**; **Figure 1D**). Other basic neural statistics were largely unaffected. Latency to peak response was greater in ASD3 relative to controls, although only modestly so with an increase in 40 ms to median latency ($p = 0.041$, Monte Carlo subsampling test; **Figure 1E**). Likewise, Fano factor (the coefficient of variation) was not statistically different in any of the patients (all $p > 0.05$, Monte Carlo subsampling test; **Figure 1F**).

To understand the neural representation of semantics and phonemics, we took an encoding model approach (Huth and Gallant, 2016; Goldstein et al., 2024; Goldstein, Wang, et al., 2023; Tang et al., 2023; Zada et al., 2024) that we and others have adapted for use in single neurons (Franch et al., 2025; Jamali et al., 2024;. Khanna et al., 2024). We used cross-validated Poisson ridge regression to predict each neuron's spike count for a given word from its dimensionality-reduced non-contextual Word2Vec embeddings (Mikolov, et al., 2013) or contextual GPT-2-Large (Layer 25) embeddings (Radford et al., 2019), and included word duration and embedding-duration interactions as co-regressors (see **Methods**; **Figure 1G**). We also fit Poisson Ridge Regression models using word-level phonemic embeddings, word duration, and their interactions (e.g., Khanna et al., 2024; **Figure 1G**). For models with semantic embeddings, we used principal component analysis (PCA) on GPT-2 and Word2Vec embeddings to ensure the same number (100) of predictive dimensions in regression models with GPT-2 or Word2Vec embeddings. A neuron was fit by the model if it exhibited a significant positive log-likelihood improvement over feature-shuffled models (ΔLLH) and a positive pseudo adjusted R^2 (see **Methods**).

Overall, we find robust encoding of semantics in autistic and control patients using both Word2Vec and GPT-2 embeddings (**Figure 1H-J**). Across both groups of patients, the contextual (GPT-2) embedder fit more neurons than the non-contextual one (Word2Vec), and both semantic models fit many more neurons than the phonemic model (all $p < 0.001$, one-sided Wilcoxon signed-rank test comparing percent of fitted neurons per patient between semantic and phonemic models, **Figure 1H**). Between semantic models, GPT-2 had significantly better fit than Word2Vec in both control and autistic patients ($p < 0.001$ and $p < 0.01$, one-sided Wilcoxon signed-rank test between ΔLLH of fitted neurons in each semantic model, **Figure 1I**).

Additionally, each semantic model performed substantially better than phonemic models in both patient groups, likely due to an intrinsic preference for semantics relative to phonemics in the hippocampus (Quian Quiroga et al., 2005 and 2009; Kolibius et al., 2023; **Figure 1J;** GPT-2 shown, $p < 0.001$ for both Word2Vec and GPT-2, one-sided Wilcoxon signed-rank test comparing GPT-2 model error, penalized Poisson AIC).

We have also shown that semantics remains the dominant driver of neural responses in the hippocampus even when accounting for a variety of linguistic features including word frequency, word order in sentence and clause, number of opening and closing nodes, and semantic and phonemic embeddings (using an approach developed in Franch et al., 2025). We replicate this result in both autistic and control patients (**Extended Data Figs. 3-4**). Semantic encoding model performance (ΔLLH) and explained variance (pseudo R^2) did not differ between autistic and control patients, suggesting intact neural encoding of semantics in autism (median pseudo $R^2 = 0.16$, 0.14, 0.24, and 0.15 for control patients and ASD1-3 respectively; $p = 0.15$, 0.96. and 0.26 for ASD1-3 respectively, Monte Carlo subsampling test; **Figure 1K**). Together, these

findings indicate that the hippocampus preferentially encodes semantic over phonemic information, and single neuron encoding of these linguistic features in autism is similar to controls.

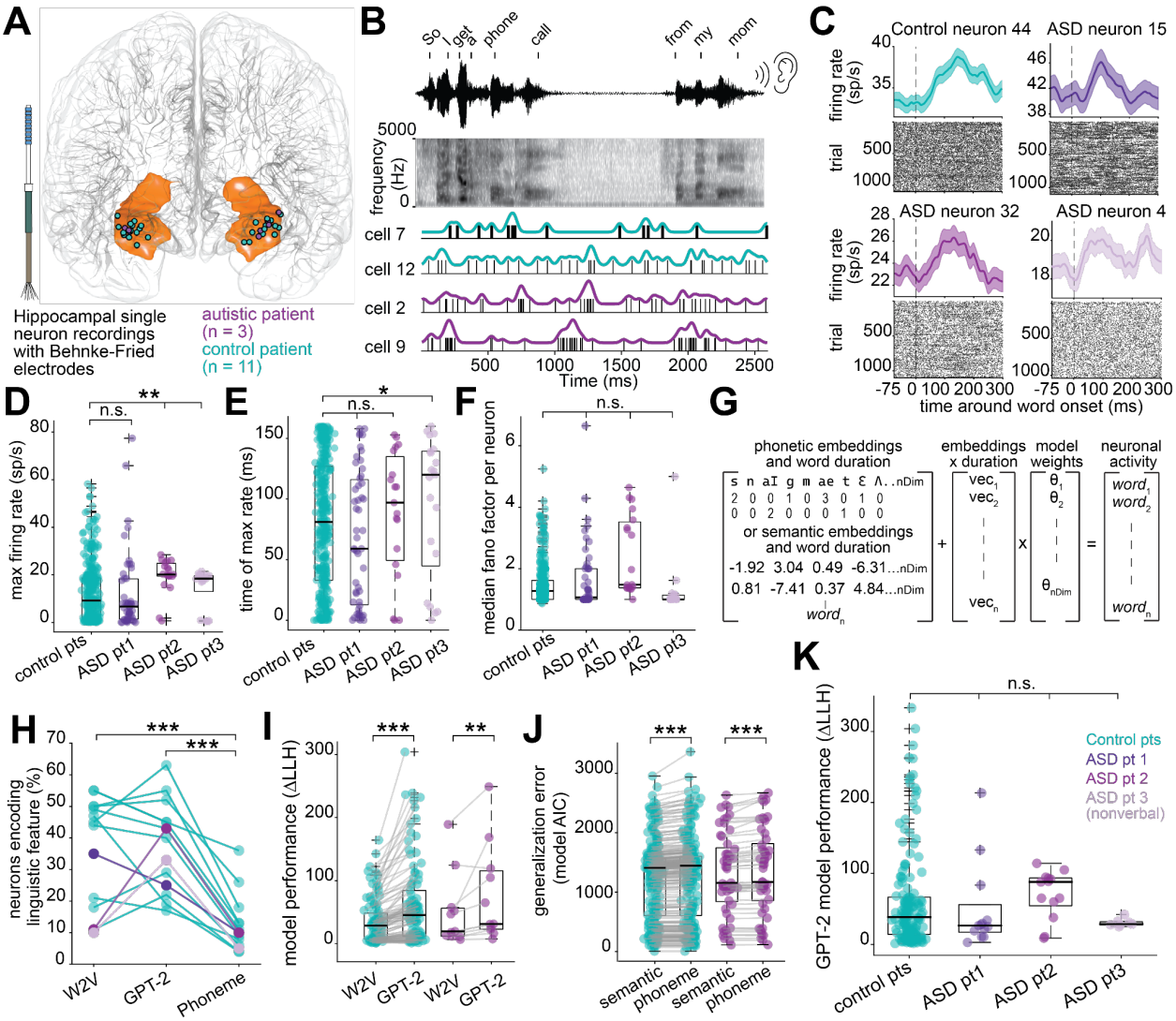

Figure 1. Preserved single neuron semantic and phonetic encoding in autism. A, Electrode recording location of hippocampal neurons from 11 control patients and 3 patients with autism. **B,** Continuous spiking activity from four example hippocampal neurons from control patient 7 and autistic patient 2 during words heard during the experiment, as shown in the spectrogram. **C,** Peri-stimulus time histograms and raster plots demonstrating neural responses to word onsets from four distinct hippocampal neurons in four different patients. Dashed lines represent word onset. Plots display mean firing rate ±SEM shaded. **D,** For each neuron (circle), the peak word-averaged firing rate following word onset. Autistic patients 2 and 3 had higher firing rates than controls ($P < 0.01$, two-sided randomization test on medians using 5,000 neuron-matched resamples from controls). **E,** For each neuron, the time after word onset that peak word-averaged firing rate occurred. ASD3 had a modest increase in latency relative to controls ($P = 0.04$, two-

sided randomization test on medians using 5,000 neuron-matched resamples from controls). **F,** For each neuron, the median fano factor across all words that occurred at least ten times (n = 66 words). **G,** Regression equation used to fit an individual neuron's spike count from word embeddings or phonetic embeddings, word duration, and their pairwise interactions. **H,** For each patient (circle), their percentage of neurons fit by the regression model in **G** using semantic embeddings from Word2Vec or GPT-2 layer 25 or IPA phonemic embeddings. The percentage of neurons fit by phonetic embeddings was significantly lower relative to semantic embedding models ($P < 0.001$, one-sided Wilcoxon signed-rank test). **I,** Log-likelihood improvements (ΔLLH; model performance) for fitted neurons (n = 109) from GPT-2 and Word2Vec semantic encoding models. Word2Vec performance is significantly lower than GPT-2 in control and autistic patients ($P < 0.001$, one-sided Wilcoxon signed-rank test). **J,** Model error (penalized Poisson AIC, EDF-based) per neuron for phonetic and semantic embedding models (385 neurons in control patient group; 91 in autistic patient group). AIC is consistently lower for semantic models (GPT-2 shown) across control and autistic patients ($P < 0.001$, Wilcoxon signed-rank test). **K,** Log-likelihood improvements (ΔLLH; model performance) for fitted neurons (n = 188 across all patients) from Poisson ridge regression predicting neuronal spike counts from the first 100 PCs of semantic (GPT-2 layer 25) embeddings using the equation in **G**. Autistic patient performance is comparable to controls ($P = 0.15$, 0.96. and 0.26 for ASD1-3 respectively, one-sided Monte Carlo subsampling test on medians using 5,000 neuron-matched resamples from controls).

Altered semantic contextualization in ASD

Individual word meanings can be thought of as points in a high-dimensional space, where the angle between vectors corresponds to semantic similarity (Mikolov et al., 2013; Devlin et al., 2018; Radford et al., 2019; **Figure 2A**). For example, the semantic distance between 'cat' and 'spoon' will be larger than that for 'cat' and 'tiger.' When words appear in context, their meanings change - sometimes modestly, sometimes profoundly - a process known as contextualization. Contextual changes in word meaning are captured in large language models such as GPT-2 (Radford et al., 2019).

To understand if neural population activity also uses vectorial distance to capture the contextual semantic relationship between words, we compute cosine distance on the responses of a population of neurons to ask whether *neural embedding distances* are correlated with semantic embedding distances (Franch et al., 2025). We found that, in both control and autistic patients, neural distance recapitulates semantic distance, as reflected by significant positive correlations between neural and GPT-2-derived semantic distances across word pairs (all $p < 0.001$; **Figure 2B**). Autistic patients' neural-semantic distance correlations matched those of the control patients ($p = 0.91$,0.63, and 0.45, Crawford-Howell significance test; **Figure 2B**). This lack of a difference is important because it argues against the possibility that the major difference between autistic and control patients is simply greater noise in the autistic population, such as may be caused by failure to attend to speech or to noisy internal representations.

The same word can have different meanings depending on the context in which it is spoken, known as polysemy. We next wondered how well control and autistic patient's neural population codes were tracking the meaning of a word across contexts. For each word that occurred at least twice (n = 396 words), we quantified polysemy as the cosine distance between

GPT-2 layer 25 embedding vectors across repeated occurrences of each word (see **Methods;** Cruse etal., 1986; Landauer, 2001; Ethayarajh, 2019). The most polysemous word in our dataset was 'through' (e.g., '*going through my head*' or '*walking through the camp*'; **Figure 2C**). We computed a word's neural polysemy as the median cosine distance between neural population responses to repeated occurrences of the same word. We then computed the correlation between neural polysemy and embedding-based polysemy across words (**Figure 2D**). A positive correlation indicates that neural activity changes more when a word's meaning shifts more across contexts, and changes less when its meaning remains stable. In both control and autistic patients, we find a positive correlation between neural polysemy and word polysemy (all $p < 0.005$; **Figure 2D**) and autistic patients' correlations were comparable to controls ($p = 0.67$, 0.18, and 0.54, Crawford-Howell significance test). Like the results presented above, these results are important because they demonstrate that core principles of semantic coding - including semantic relationships and context-dependent shifts in meaning - are preserved, and largely match quantitatively, in our autistic patients.

The specific strength of mappings between the past and current words in transformer-based LLMs is given by the ***attention pattern grid*** (**APG**, Vaswani et al., 2017; Vig, 2019). These attention weights determine how contextual information from prior words contributes to the current word's representation, thereby shaping the model's contextual semantic encoding. We have previously used the logic of APGs to quantify the effects of lexical contextualization on neural responses to single words (Katlowitz et al., 2025). In that study, we found that neural responses to a given word are weighted by the embedding of the words that contextualize it (**Figure 2E**). Here, we used this same approach to determine whether semantic contextualization is altered in ASD, using our control patients as a baseline condition.

We next created 37 latent LLM APGs, one for the initial embedding and then each of the 36 layers of GPT-2 and compared each one to our neural APG from control and autistic patients (see **Methods**; **Figure 2F**). In essence, the APG is a data-derived vectorial representation of how strongly each prior word influences a given word, in its actual context, and so the match between a neural and LLM-derived APG can serve as an index of how closely the brain matches the "ground truth" contextualization vector. We tested the correlations across a range of local contextual windows (1-20) for each layer. The context windows reflect the number of words before the current word that are allowed to contextualize the current word. In control patients, we find that the mean correlation between neural and LLM APGs across words is positive for all layers and contextual windows but can vary greatly as a function of both (**Figure 2F-G**; Katlowitz, 2025). However, in the three autistic patients, we find reduced contextualization at all window sizes except the shortest ones and at all layers. In other words, in the autistic patients, lexical contextualization is preserved, and in largely the same way as in control patients, but is reduced in the magnitude of its effects, especially more than a few words in the past.

These effects can be observed even more clearly when considering the graph marginals (**Figure 2G**). All patients exhibit a decrease in correlation across word window size, especially beyond the fifth previous word in control patients (**Figure 2G-left**), consistent with the

expectation that more distant words exert weaker influence on the current word's representation and therefore contribute less to contextual semantic encoding. In contrast, autistic patients showed a sharp drop in correlation immediately after the preceding word, suggesting a more restricted temporal integration of contextual information (**Figure 2G-left**). In control patients, neural-APG correlation peaked at layer 26, a late transformer layer associated with deep contextual semantic integration, whereas autistic patients showed peak attention alignment at earlier, less contextualized layers (stars - layers 8, 1, and 1 for ASD1-3 respectively, **Figure 2G-right;** Ethayarajh 2019; He et al., 2024).

Autistic patients 2 and 3 had a non-significant negative correlation with APG values from GPT-2 layer 26, while ASD1 and control patients had significant positive APG correlations with this layer ($p < 0.05$, Pearson correlation; **Figure 2G-right and Figure 2H**). We took the median APG values for up to five words back from every word across control patients to get one distribution of APG values for the control group. For autistic patients, we took the median APG values from five words back from all the autistic patients to get one distribution of APG values for the autistic group (**Figure 2I**). We find that the autistic patients have a broad distribution compared to both the control-neural and LLM APG values (**Figure 2I**). Indeed, the control patient APG values are positively correlated with LLM APG but the autistic patient's APGs are not significantly correlated with either the control patients or LLM (**Figure 2I**; autistic neural APG distributions and their relationship to control patients and LLM APG values are comparable even if only autistic patients 2-3 are used; **Extended Data Fig. 5**). We also find that both the LLM and control patients most frequently assign the *highest* contextual weight to the immediately preceding word (i.e., '*red*' as the most contextualizing word in '*red balloon*'), whereas autistic patients show a broader distribution, with the most contextualizing weights often extending to more distant words up to five words back (**Figure 2J-K**). Together, these results indicate that neural contextual weighting in autistic patients is less precisely aligned with the statistical structure captured by the LLM and observed in control patients. Even when autistic patients identify the same previous word as most contextualizing, the sign and/or magnitude of the corresponding APG value differs from both the LLM and control patients, reflecting altered scaling of contextual semantic influence rather than a complete loss of contextual semantic sensitivity (**Figure 2E-bottom and Figure 2K**).

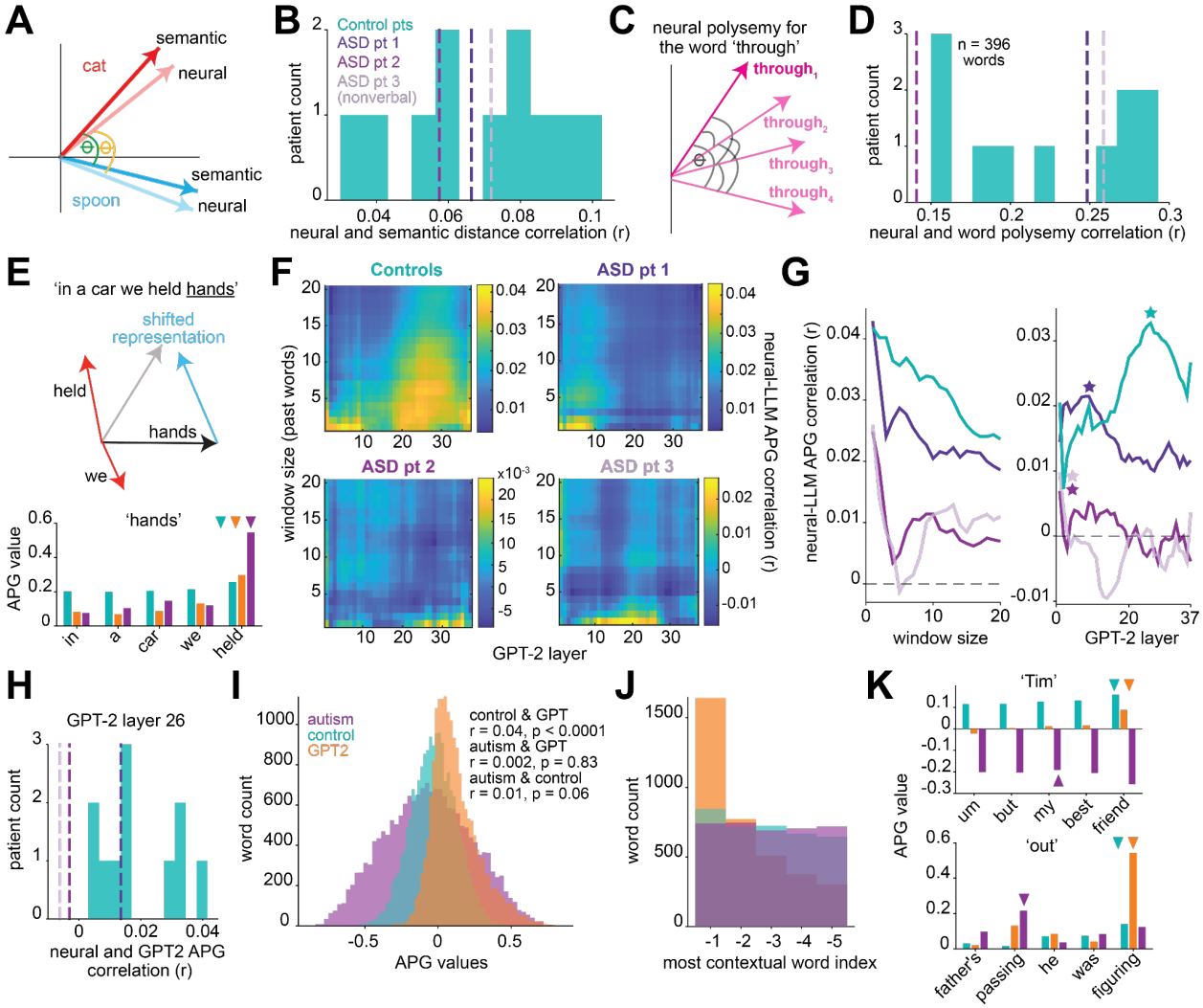

Figure 2. Reduced prior-word context integration in semantic neural coding in autism. A, We define semantic distance as the angular distance in a high dimensional space between two semantic vectors (embedding values for each word; green theta). We define neural distance in the analogous manner, where each word's neural embedding is the vector of firing rates from all neurons for that word (yellow theta). **B,** For each patient, the Pearson correlation between neural and semantic embedding (GPT-2 layer 25) distances between all 8,514,001 word pairs (all $p < 0.001$). Autistic patient correlations are shown as dashed lines to visualize their relation to control patients. **C,** Schematic showing how we define polysemy as the median cosine distance in neural population or embedding space between different occurrences of the same word. **D,** For each patient, the Pearson correlation between neural and word polysemy ($n = 396$ words; all $p < 0.001$). Autistic patient correlations are shown as dashed lines to visualize their relation to control patients. **E,** Top - Vectorial diagram shows how adjacent words can modify the neural vectorial representations of words (e.g., "held" appearing in the context of "hands" shifts the firing rate vector for "hands" to have a more similar cosine distance to the vector for "held"; "hands" vector shifts from black to gray). Bottom - A real example sentence of the APG values computed for six words occurring before the word "hand" from GPT-2 or neural embeddings from each patient group (median across patients). Triangles indicate the most contextualizing word for "hands". **F,** The correlation between neural and GPT-2 APG values computed for each GPT-2 layer (x-axis) and up to 20 previous words (y-axis). The top left plot shows the median correlation values taken

across all control patients. **G,** From the data in F, the neural-APG correlation values plotted across different window sizes (left) and GPT-2 layers (right). The teal line reflects median correlation values across control patients. Stars reflect the layer of maximum correlation; for visibility, stars for ASD patients 2 and 3 (layer 1) are plotted slightly to the right. **H,** For each patient, the Pearson correlations between neural and GPT-2 APG values (n = 18,015 APG values) computed from layer 26 and for the previous five words. Autistic patient correlations are shown as dashed lines to visualize their relation to control patients. **I,** Histograms of 18,015 APG values computed separately from GPT-2 layer 26, control patients (median across patients), and autistic patients (median across patients). **J,** Histograms indicate which preceding word (1–5 words back) exerted the strongest contextual influence on the current word based on maximal APG values (n = 4,128 words). **K,** Real examples of APG values computed for the five words before "Tim" and "out" from GPT-2 layer 26 or neural embeddings from each patient group (median across patients). Triangles indicate the most contextualizing word.

Reduced dimensionality of the predictive neural subspace for semantic coding in autism

We next asked how the hierarchical structure of semantic representations across GPT-2 layers is reflected in neural coding, and whether this organization is disrupted in autism. First, we used the same regression modeling as shown in Figure 1G to predict spike counts from semantic embeddings from each layer of GPT-2. We find that, relative to controls, autistic patients 1 and 3 have a lower percentage of neurons fit by the model, and that this effect is consistent across layers of GPT-2 (**Figure 3A**). Moreover, single neuron responses in each autistic patient aligned *best* with semantic embeddings from earlier, less contextual layers of GPT-2 (layers 9, 15, and 12), whereas neurons from control patients aligned best with layer 27 (**Figure 3B;** control layers ranged from 15-37). Embeddings from earlier layers are more strongly driven by lexical identity, word frequency, and part of speech, whereas layers 24 and beyond increasingly reflect semantic similarity and predictive probability (Ethayarajh 2019; He et al., 2024). To determine whether this shift toward earlier-layer alignment in autism was significantly different from controls, we divided the dataset into ten contiguous segments and performed cross-validated regression within each segment. Across models, neural activity in autistic patients showed a consistent bias toward earlier layers relative to controls ($p < 0.001$; Wilcoxon rank-sum test comparing each autistic patient's values to controls across models; **Figure 3B**). Notably, the association between mid-to-late layers and semantic encoding is well established in other studies of allistic adults, so the autistic data represent a genuine exception to a larger pattern (Caucheteux etal., 2022; Goldstein, Ham, et al., 2022; Schrimpf et al., 2021).

We next asked how the geometry of semantic coding in the hippocampus may be altered in autism. For each word, the pattern of activity across neurons can be represented as a point in high-dimensional neural space, with dimensionality equal to the number of recorded neurons (**Figure 2A**). Prior work has shown that task-related population activity often lies in a low-dimensional subspace relative to the number of recorded neurons or task variables, and that these latent dimensions capture the neural coding of behaviorally relevant features (Gao et al., 2017; Cunningham and Yu, 2014; Ebitz and Hayden, 2021). To identify the low-dimensional neural subspace that is linearly predictive of semantic structure, we applied cross-validated reduced rank regression (RRR) to map neural population activity onto GPT-2 semantic embeddings in

each patient (**Figure 3C**; using 30-dimensional embeddings; results were consistent across models using different numbers of GPT-2 principal components; see **Methods**; Izenman 1975; Franch et al., 2025).

We quantified model performance as the cross-validated variance explained (1 – NSE) across predictive subspace dimensionalities (ranks = 0 - 30). All models showed near-zero performance at rank 0 (predicting the mean), confirming an unbiased baseline. Across ranks, predictive performance increased monotonically before reaching a plateau for each patient. Two autistic patients showed significantly lower model performance across ranks compared to each control patient, whereas ASD patient 1 performed comparably to controls ($p < 0.001$, one-sided permutation test; **Figure 3D**). This pattern was consistent across all GPT-2 layers (**Figure 3E**). Across patients, decoding performance was highest for embeddings from mid-to-late GPT-2 layers; however, performance in ASD patients 2 and 3 remained significantly lower than in controls and ASD patient 1 ($p < 0.001$, one-sided permutation test; **Figure 3E**). In other words, neural decoding of semantics was significantly reduced in two autistic patients compared to controls.

We next examined the latent structure of the predictive subspace in control and autistic patients. Model rank in RRR corresponds to the number of orthogonal latent neural dimensions contributing to the predictive mapping from neural activity to the embedding space. Thus, rank provides a measure of how many independent population axes are required to support semantic prediction. Optimal model rank was defined as the smallest rank achieving performance within one standard error of peak cross-validated accuracy, providing a principled estimate of the minimal predictive neural dimensionality required by each patient. When predicting GPT-2 layer 37 embeddings, ASD patients 2 and 3 exhibited lower optimal ranks than control patients and ASD patient 1 (dashed lines, **Figure 3D**). Across individuals, optimal rank increased for higher GPT-2 layers (from approximately layer 11 onward), indicating that deeper, more contextual language representations required a more distributed neural predictive subspace (**Figure 3F**). However, optimal rank remained significantly reduced across GPT-2 layers in ASD patients 2 and 3 relative to controls, suggesting that semantic prediction in these individuals relied on fewer independent neural population dimensions ($p < 0.001$, one-sided Wilcoxon signed-rank test; **Figure 3F**).

While optimal rank estimates how many predictive neural dimensions are required, it does not capture how predictive variance is distributed across those dimensions. To address this, we quantified the effective dimensionality of the predictive weight subspace using the participation ratio (using the median optimal rank of control patients for all patients; see **Methods**), which measures how evenly predictive variance is spread across latent axes. Intuitively, effective dimensionality distinguishes between a subspace in which predictive variance is concentrated along a small number of dominant dimensions and one in which variance is more uniformly distributed across many axes. For each patient, effective dimensionality increased across GPT-2 layers, indicating that predictive variance became more evenly distributed for higher-level semantic embeddings (**Figure 3G**). Notably, effective

dimensionality was significantly reduced in all autistic patients across layers ($p < 0.001$, one-sided permutation test; **Figure 3G**), indicating that semantic prediction relied on a more compressed predictive geometry, with variance concentrated along a limited set of dominant neural axes.

These findings raise the possibility that autism may be associated with a bias toward lower-dimensional predictive representations of semantic information (**Figure 3H**). This compression is not inherently detrimental, as demonstrated by ASD patient 1, whose decoding performance matched that of controls, suggesting that task-relevant semantic information can be preserved within a lower-dimensional subspace. However, when critical semantic variance is not adequately captured within this compressed predictive geometry, decoding performance may be impaired, as observed in ASD patients 2 and 3. In contrast, control patients showed higher-dimensional predictive subspaces, which may allow the brain to simultaneously represent multiple aspects of a word's meaning - such as its predictability, relationship to surrounding words, and role within the broader discourse - resulting in a richer and more detailed semantic representation of the current word (**Figure 3H**). Across all patients, higher effective dimensionality indicated that predictive variance was distributed across a larger set of independent latent dimensions, increasing representational capacity and enabling more flexible and robust semantic prediction (**Figure 3E-H**).

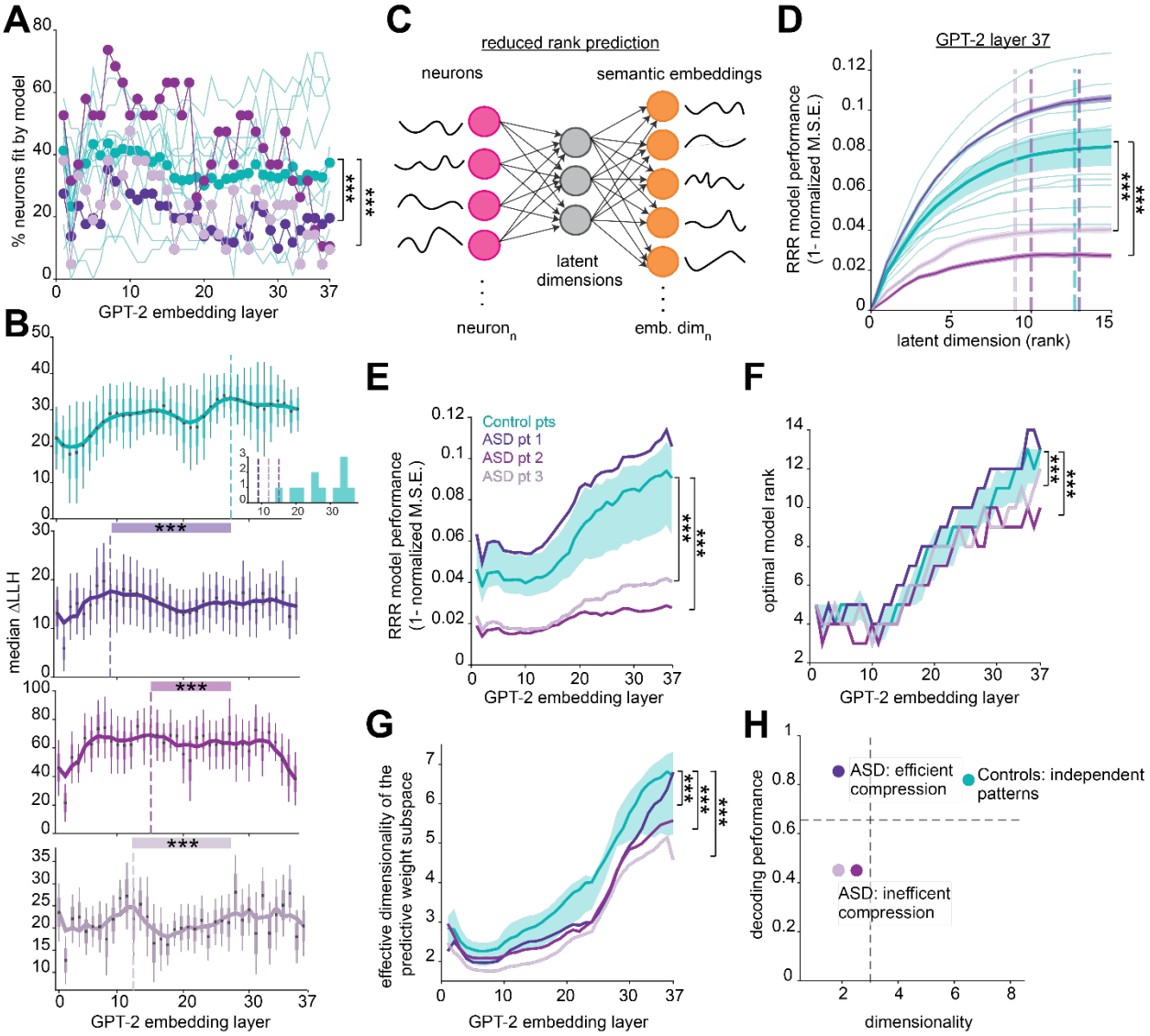

Figure 3. Reduced dimensionality of semantic coding in autism. A, Percentage of neurons fit by linear regression models using the first 100 PCs of semantic embeddings from each layer of GPT-2 large. Light teal lines show individual control patients; dark teal circles denote the median across controls. Two autistic patients have significantly fewer neurons fit by the model relative to controls ($P < 0.001$, one-sided Wilcoxon signed-rank test comparing patient percentages to control median). **B,** The median model performance (ΔLLH) across neurons for each patient and layer (median and SEM). The bolded line represents the median smoothed with a gaussian of width 5 and dashed lines indicate the maximum of the fitted line. The insert shows the GPT-2 layer with best performance for each patient. Each autistic patient has peak performance at earlier layers (layers 9, 15, and 12) of the model compared to controls (layer 27; $P < 0.001$, Wilcoxon rank-sum test comparing each autistic patient's values to controls across models fit on 10 different contiguous sets of the data). **C,** Schematic of reduced-rank regression (RRR) predicting semantic embeddings from neural population activity by projecting activity onto a low-dimensional set of predictive latent dimensions that explain variance in the predicted embedding space. Schematic adapted from those in Wu and Pillow, 2025. **D,** Model performance across 15 latent dimensions (ranks) from RRR predicting 30-dimensional (top 30 PCs) GPT-2 layer 37

semantic embeddings from neural firing rate responses to words. Models were fit separately for each patient, then averaged across control patients for the control group. Lines represent mean performance ±SEM. Model performance was significantly lower for two autistic patients compared to controls ($P < 0.001$, one-sided permutation test). Dashed lines indicate the number of dimensions for optimal performance; rank = 13 for controls and ASD pt1, rank = 10 and 9 for ASD patients 2 and 3 respectively. **E,** For each GPT-2 layer, optimal RRR model performance is plotted. The dark teal line shows the median across control patients, and shading reflects the interquartile range. Model performance was significantly lower for two autistic patients compared to controls ($P < 0.001$, one-sided permutation test). **F,** For each GPT-2 layer, the rank of optimal model performance is plotted. The dark teal line shows the median across control patients, and shading reflects the interquartile range. Model rank for two autistic patients was consistently lower relative to controls across layers ($P < 0.001$, one-sided Wilcoxon signed-rank test). **G,** For each GPT-2 layer, the dimensionality of neuron-weight patterns used for semantic prediction is plotted. The dark teal line shows the median across control patients, and shading indicates the interquartile range. Effective dimensionality of each autistic patient was significantly lower than control patients across layers ($P < 0.001$, one-sided permutation test). **H,** Predictive neural dimensionality reflects a trade-off between compression and representational coverage. A lower-dimensional predictive subspace can support strong performance when task-relevant signals align with dominant latent axes, whereas a higher-dimensional predictive subspace distributes variance across multiple independent axes, enabling greater flexibility and generalization.

Altered population-level coding of word surprisal and concreteness in autism

Predictive coding theories propose that neural activity reflects the discrepancy between expected and observed input (Rao and Ballard, 1999; Feldman and Friston, 2010). In language, this prediction error can be quantified using word surprisal, which measures how unexpected a word is given its context (Levy, R. 2008; Weissbart et al., 2020). We computed surprisal using GPT-2 as the negative log probability assigned to each observed word given its preceding context, providing a model-based estimate of prediction error (see **Methods; Figure 4A**). We identified the top and bottom 5% of words to categorize the most surprising and most expected words, respectively. Examples of the most surprising words include, 'bungee', 'apocalyptic' and 'typewriter', while the least surprising words include, 'call', 'hand' and 'birthday.' To isolate neural sensitivity to surprisal, we residualized each neuron's firing rates with respect to log word frequency and word duration across all words, as both variables were correlated with surprisal (Pearson $r = -0.49$ and 0.42, respectively).

Across patient groups, at least 35% of neurons showed a significant change in firing rate between the most and least surprising words (controls: 39%; ASD1: 53%; ASD2: 37%; ASD3: 52%; $p < 0.05$, Wilcoxon rank-sum test with FDR correction across all 476 neurons), indicating that a substantial fraction of hippocampal neurons were sensitive to word predictability. Notably, this modulation was consistently directional: single hippocampal neurons exhibited significantly higher firing rates to surprising compared to expected words, a pattern observed across control patients and all autistic patients (**Figure 4B–C;** $p < 0.001$, Wilcoxon signed-rank test), and

consistent with prior findings from studies of LFP and BOLD signals (Schneider and Blank, 2026; Goldstein et al., 2022; Weissbart et al., 2020; Willems et al., 2016).

Despite this intact single-neuron prediction error signal, population-level decoding of surprising versus expected words was significantly reduced in each autistic patient compared to controls, suggesting that while individual neurons encode surprisal, this information is less efficiently organized across the neural population in autism (**Figure 4D;** $p < 0.01$, one-sided permutation test). Although single neurons exhibit prediction-error sensitivity, increased shared variability across neurons (i.e., noise correlations) may increase redundancy and limit separability between surprising and expected words. Such altered organization is consistent with our APG findings in autistic patients (**Figure 2E-K)**, together pointing to atypical contextual integration rather than an absence of prediction error signaling.

Some individuals with autism might have a vocabulary that is less semantically rich than non-autistic peers, understanding concrete terms like 'cookie' while struggling to understand more abstract terms like 'dessert' (Graves et al., 2022; Andreou et al., 2025). Concrete words (e.g., 'cookie') are typically grounded in perceptual features and can be understood with minimal contextual information, whereas abstract words (e.g., 'dessert') rely more heavily on contextual and relational information for meaning (Schwanenflugel, 1991; Barsalou, 2008). Therefore, we next examined whether neural coding of abstract and concrete words was different in autism. We obtained concreteness ratings for nouns in our dataset from Brysbaert et al. (2014), which provides human-rated concreteness scores (1 = least concrete; 5 = most concrete) for 39,954 English words (see **Methods**). We identified the top and bottom 20% of words to categorize the most concrete and most abstract nouns, respectively (**Figure 4E**). Examples of abstract words were 'something', 'moment', and 'kind' while some of the most concrete words include 'grenade', 'knees', and 'earth.'

Compared to word surprisal, fewer neurons were sensitive to word concreteness, with only 10% of neurons showing a significant change in firing rate between the most concrete and most abstract words (controls: 10%; ASD1: 16%; ASD2: 11%; ASD3: 10%; $p < 0.05$, Wilcoxon rank-sum test with FDR correction across all 476 neurons). Single neurons did not exhibit significant directional changes in firing rate between abstract and concrete words, with the exception of ASD2 who had higher firing rates for abstract words (**Figure 4F;** $p < 0.01$, Wilcoxon signed-rank test). Hippocampal neurons appear to be more tuned to predictability (surprisal) than to semantic features tied to sensory grounding (concreteness).

Although word concreteness exerted only a weak influence on single-neuron firing rates, population-level decoding revealed differences between control and autistic patients. In two autistic patients, neural population responses to concrete and abstract words were more linearly separable, as reflected by significantly higher cross-validated decoding accuracy compared to control patients and ASD3 (**Figure 4G**; $p < 0.001$, one-sided permutation test). In contrast, the most severely affected autistic patient showed lower decoding performance, comparable to controls, indicating that this increased separability was not uniformly present across autistic individuals. Together, these findings suggest that autism may involve reorganization of semantic

dimensions at the population level. Whereas surprisal-related signals were less separable in autistic patients, concreteness representations were more separable in some individuals, indicating that semantic dimensions may be differentially represented within neural population geometry. Greater neural separability between concrete and abstract concepts in some autistic patients may reflect stronger grounding of concrete words in consistent, multisensory experience, which could contribute to the relative preservation of concrete word comprehension observed behaviorally in autism.

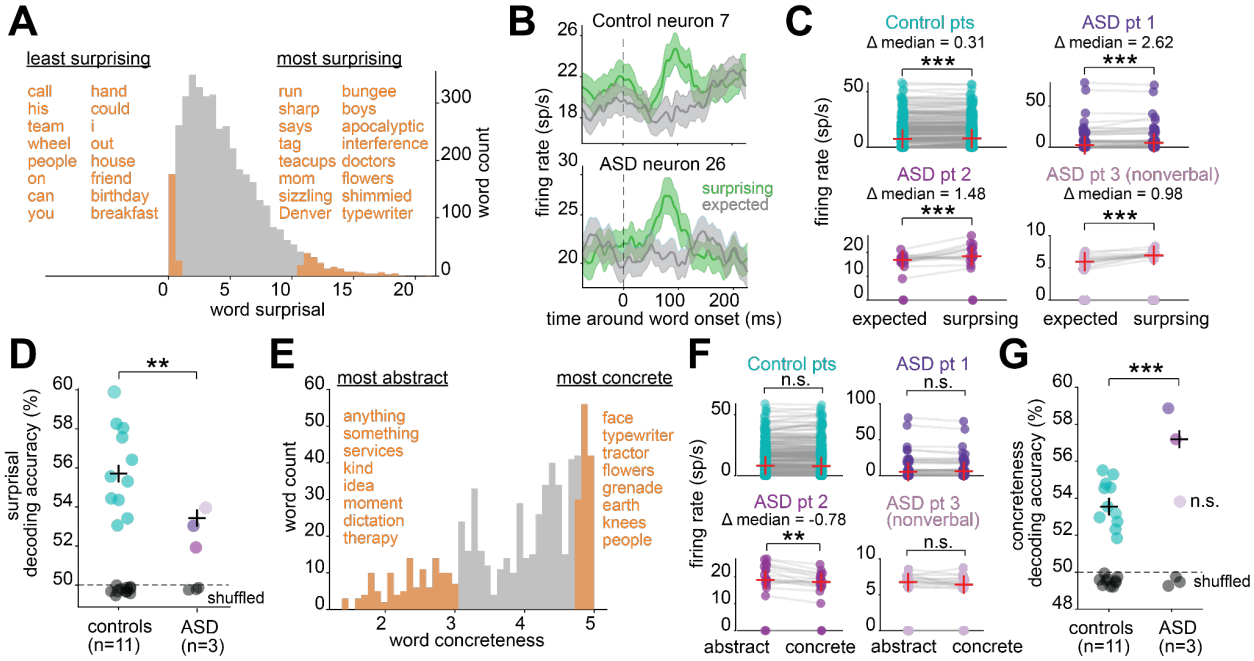

Figure 4. Population coding of word surprisal and concreteness is altered in autism. A, Word surprisal values for all words in the data except the first word (n = 4,127). 205 words in orange reflect the top (surprising) and bottom (expected) 5% of surprisal values. **B,** Example peri-stimulus time histograms of firing rate responses to surprising or expected words from a hippocampal neuron in a control and autistic patient. **C,** For each neuron (circle) of control patients and each autistic patient, its word-averaged firing rates for surprising and expected words is plotted. Crosses reflect the median rate for each word type across neurons. Surprising words evoked significantly higher firing rates in each patient ($P < 0.001$, Wilcoxon signed-rank test on residual rates). **D,** For each patient, linear decoding accuracy (Support Vector Machine classifier) for surprising and expected words from neural population activity, for models using real and shuffled (black) data. Crosses reflect the group median; dashed line represents chance. Model accuracy was significantly reduced in autistic patients ($P = 0.002$, one-sided permutation test). **E,** Word concreteness values for all nouns in the data (n = 652). 124 words in orange reflect the top (concrete) and bottom (abstract) 20% of concreteness values. **F,** For each neuron (circle) of control patients and each autistic patient, its word-averaged firing rate for abstract and concrete words is plotted. Crosses reflect the median rate for each word type across neurons. Abstract words evoked significantly higher firing rates in autistic patient two ($P < 0.01$, Wilcoxon signed-rank test). **G,** For each patient, linear decoding accuracy for concrete and abstract words from neural population activity, for models using real and shuffled (black) data. Crosses reflect

the group median; dashed line represents chance. Model accuracy was significantly higher in 2/3 autistic patients ($P < 0.001$, one-sided permutation test).

Reduced neural-linguistic feature alignment in autism

Thus far, we examined how neural activity relates to individual linguistic features, including contextual semantic embeddings, word surprisal, concreteness, and polysemy. However, language comprehension involves the simultaneous integration of multiple features. We therefore asked whether neural population activity reflects a shared structure across these linguistic dimensions, and whether this neural–linguistic alignment differs in autism. To address this, we used canonical correlation analysis (CCA), which identifies shared structure between neural population activity and a multidimensional linguistic feature space (Hotelling, 1936). For each patient, we applied cross-validated CCA to word-evoked firing rates across all neurons and 13 linguistic features, including the first 10 principal components of GPT-2 semantic embeddings, as well as word surprisal, concreteness, and polysemy (see **Methods**; The results below were consistent across models using different numbers of principal components of GPT-2 embeddings and when using the full embeddings).

Along the first canonical component, neural activity and linguistic features were significantly correlated in all control patients and in ASD1, indicating a shared neural-linguistic representational axis (**Figure 5A**). In contrast, ASD patients 2 and 3 exhibited markedly weaker correlations that did not reach significance. Permutation testing confirmed that the cross-validated first canonical correlation exceeded the shuffled null distribution in controls and ASD1 ($p < 0.001$; **Figure 5B**), but not in ASD patients 2 and 3, indicating a loss of reliable shared linear structure.

Do ASD patients rely on different linguistic feature combinations to define the neural-linguistic axis? We compared the orientation of the canonical weight vector across patients after sign alignment and unit normalization (see **Methods;** PCA projections of unit-normalized weight vectors were used only for visualization; **Figure 5C**). We quantified similarity between patients using the angle between unit weight vectors in the 13-dimensional feature space. Control patients exhibited relatively consistent weight-vector orientations, reflected in small control–control angles. As expected, ASD patients 2 and 3 showed significantly larger angular deviations from controls (**Figure 5C**; $p < 0.001$, one-sided bootstrap test against control-derived null), whereas ASD1 fell within the expected range of control variability (**Figure 5C**; $p = 0.79$, one-sided bootstrap test against control-derived null).

Next, we identified which linguistic features exhibit the strongest loadings on the canonical axis and tested whether this loading structure differs between controls and autistic patients. Feature loadings quantify how strongly each linguistic feature contributes to the shared neural–linguistic dimension. The magnitude reflects the feature's relative importance, while the sign indicates whether the feature varies positively or negatively along that shared axis. In control patients, semantic embedding features exhibited the largest loadings on the canonical axis, indicating that contextual semantic information primarily defined the shared neural–

linguistic dimension (**Figure 5D**). In ASD1, both semantic embeddings and word concreteness showed strong loadings, suggesting a broader reliance on both contextual and perceptual features (**Figure 5E**). In contrast, surprisal and polysemy contributed minimally to the canonical axis in both controls and ASD1 (**Figure 5D-E**). Loadings from ASD2 and ASD3 are shown for completeness; however, because the canonical correlations in these patients were not statistically significant, their loading patterns are not interpreted (**Figure 5F-G**). These results suggest that autism is not characterized by a uniform alteration of specific linguistic features but rather by variability in the existence and organization of a shared neural–linguistic subspace linking language features to population activity.

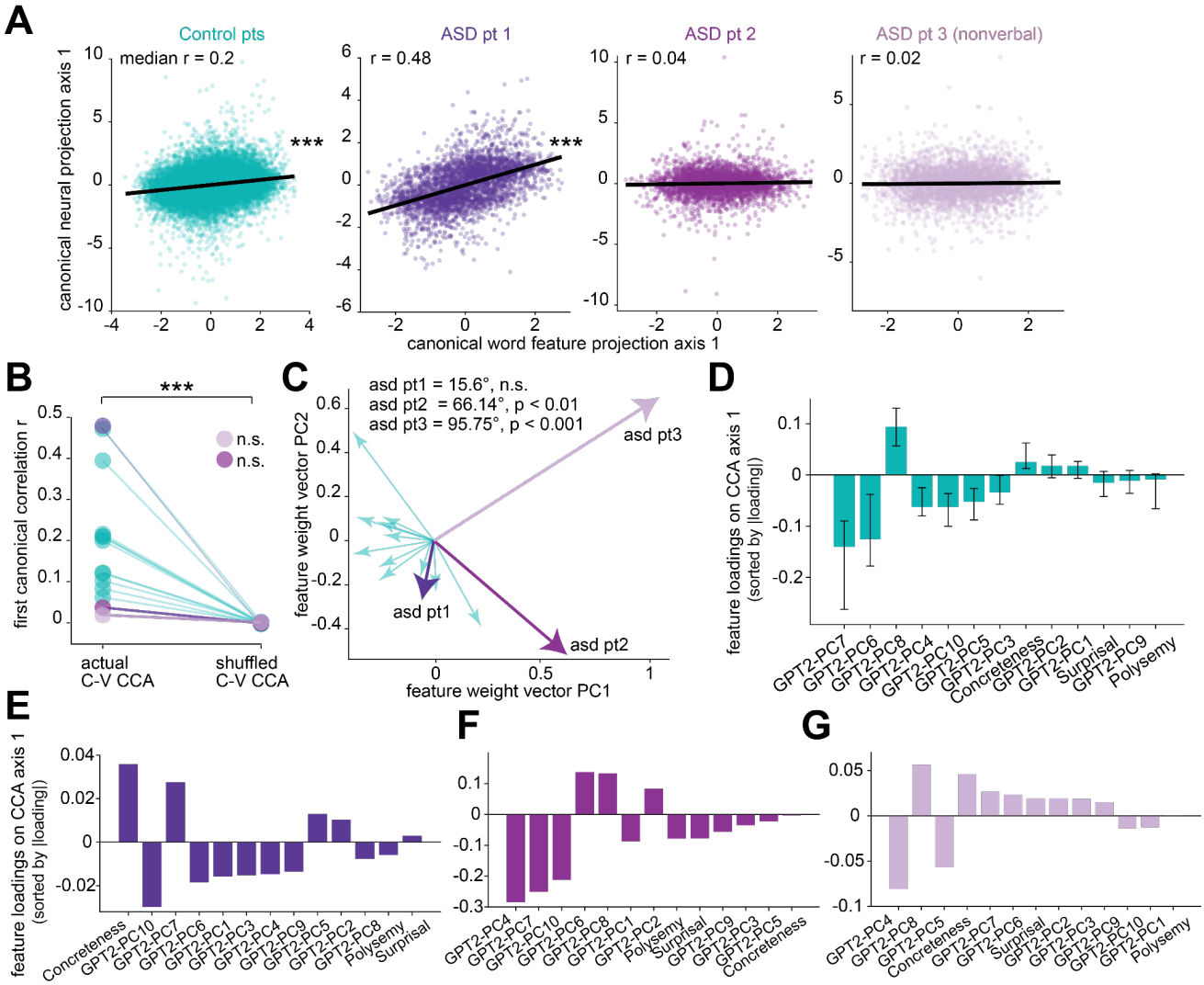

Figure 5. Absence of a shared linear neural-linguistic feature space in some individuals with autism. A, Each point represents a word, plotted by its held-out projection onto the first canonical axis of the linguistic feature space (n= 13 features) and the neural population space. Lines indicate linear fits. Control points are pooled across control patients. For each patient, the cross-validated axis-1 canonical correlation (r) quantifies the held-out association between

neural and linguistic representations. Controls and ASD1 have significant correlations ($P < 0.001$, word-label permutation test). **B,** For each patient, the mean cross-validated canonical correlation on CCA axis 1 (actual) is shown alongside the median of the permutation null distribution, obtained by shuffling words of the linguistic feature matrix ($P < 0.001$, permutation test). **C,** For each patient, their canonical feature weight vectors for CCA axis 1 after sign alignment to the control mean and unit normalization. The plot shows the relative orientation of weight vectors in feature space (PCA visualization). For each ASD patient, cosine angle between their weight vector and the mean control vector is shown; significance was assessed using a bootstrap null derived from control-control angles. **D,** Bars show the median loading (Pearson correlation between each linguistic feature and the out-of-fold canonical score on axis 1) across controls for each feature, with error bars indicating the interquartile range, sorted by absolute median loading. **E–G,** Individual autistic patients: bars show patient-specific feature loadings, sorted by absolute value. Loadings were sign-aligned to the control direction for comparability. Positive and negative values indicate the direction and strength of association between each feature and the canonical linguistic axis.

DISCUSSION

Here, we characterize neural computations for semantic coding during language comprehension in three autistic patients whose language abilities ranged from fluent to nonverbal. Despite heterogeneity in language ability, autistic patients exhibited a shared neural profile, characterized by intact core semantic representations but systematic alterations in semantic contextualization relative to controls. Autistic and control patients exhibited comparable single-neuron semantic encoding, neural population discrimination between word meanings, and context-dependent tracking of word meaning (**Fig. 1 and Fig. 2A-D**). The presence of these effects indicates that autistic patients were actively processing the linguistic content of the narratives. The quantitative similarity of these core semantic computations between control and autistic patients argues against the possibility that group differences arise from reduced attention or increased neural noise. Rather, our results suggest that the fundamental neural mechanisms supporting semantic representation during speech comprehension remain consistent in autism, while the integration of contextual information is selectively altered.

Notably, all autistic patients had reduced neural signatures of contextualization, including: (1) altered neural weighting of prior words for semantic coding a given word, (2) single neuron alignment to semantic embeddings from earlier, less contextual layers of GPT-2, (3) reduced effective dimensionality of the neural subspace predictive for semantics, and (4) reduced neural decoding of word surprisal. These findings align with models of altered predictive processing underlying perceptual deficits in autism (Pellicano and Burr, 2012; Brock, 2012; Mitchell and Ropar 2004; Lawson et al., 2014; Van de Cruys et al., 2014; Van Boxtel and Lu, 2013; Schneebeli et al., 2022; Noel and Angelaki, 2023).

Most importantly, the broad distribution of neural APG values in autistic patients resembles the proposed weaker, broad distribution of priors in Bayesian theories for ASD (**Figure 2I;** Pellicano and Burr 2012; Mitchell and Ropar 2004). A broad distribution of priors means expectations are less strong or less constraining, so perception depends more on incoming input than on context-based prediction. The broad APG distribution across prior words suggests that the neural system is not concentrating contextual weight on the most diagnostic recent words, but is instead spreading that weight more diffusely. In plain terms, context is still being used, but it is used in a less focused and less selective way. In a similar vein, we find robust prediction error in single hippocampal neurons for surprising words in all autistic patients, but surprisal decoding is reduced in the neural population compared to control patients, consistent with altered precision or weighting of contextual predictions (Lawson et al., 2014; **Figure 4A-D**). Together, these findings suggest not an absence of prediction-error signaling in autism, but a change in how contextual predictions and their violations are distributed across neural populations, potentially reflecting increased noise correlations or redundancy in population responses.

It remains debated whether autistic perception is better characterized by reduced top-down influences on perception or, alternatively, enhanced bottom-up sensory-perceptual processes. Our findings are more consistent with reduced top-down contextual influence. Single neuron phonemic and semantic encoding in autistic patients was comparable to controls (**Figure**

716 **1 and Extended Data Fig. 3B**). Moreover, neural responses in autistic patients were best
717 predicted by embeddings from earlier GPT-2 layers that capture surface linguistic structure (e.g.,
718 word form and syntax), rather than deeper contextual semantic representations. Overall, our
719 findings are broadly consistent with Bayesian predictive coding accounts proposing altered
720 weighting of prior expectations in autism, but they do not uniquely distinguish between
721 competing formulations of these theories (Pellicano and Burr, 2012; Lawson et al., 2014; Van de
722 Cruys et al., 2014; Chrysaitis and Series, 2023; Noel and Angelaki, 2023).
723 Although single neurons in autistic patients aligned most strongly with earlier GPT-2
724 layers, population decoding still successfully reconstructed later contextual embeddings,
725 indicating that contextual information is present in the neural population (**Figure 3E**). However,
726 effective dimensionality of the neural subspace predictive for semantics was significantly lower
727 in all autistic patients compared to controls (**Figure 3G**). This means that the neural patterns
728 used for predicting semantics are more redundant and less independent compared to control
729 patients, which can limit the neural representational capacity for semantic coding, as we
730 observed in ASD patients 2-3 (**Figure 3E**). Said another way, in autistic patients, neural
731 population activity is dominated by a smaller number of shared latent signals, causing neurons to
732 vary more together rather than independently. This bias towards lower effective dimensionality
733 in autistic patients could contribute to the reduced surprisal decoding and altered neural APG we
734 observed, as lower effective dimensionality means there are fewer independent coding axes,
735 which could impose less selective contextual constraint, leading to a broader distribution in the
736 neural weighting of prior words.
737 Our results also highlight heterogeneity in language ability among autistic patients. In
738 several analyses, semantic coding differed between autistic patients in how closely they
739 resembled control patients. ASD patients 2 and 3 had lower language ability than controls, and
740 their neural results often diverged from both control patients and ASD1, whose IQ and language
741 ability were within the range of the control group. In contrast to controls and ASD1, ASD
742 patients 2 and 3 showed higher firing rate responses to words (**Figure 1D**), the most altered
743 neural APG values - including negative correlations between neural and LLM-derived APGs
744 (**Figure 2G-H**) - reduced population decoding performance for semantic embeddings (**Figure**
745 **3E**), and an absence of a shared neural–linguistic feature space (**Figure 5**). These differences
746 suggest that variability in language ability may be associated with differences in how semantic
747 information is organized across neural populations. In patients with lower language ability,
748 neural representations of meaning may be less aligned with the statistical structure of language
749 and less effectively organized to support contextual integration. Notably, differences in
750 concreteness representations did not follow this same pattern. ASD patients 1-2 showed greater
751 separability of neural responses to concrete versus abstract words compared to both controls and
752 ASD3, indicating that this effect was not explained by language ability (**Figure 4G**). This
753 finding suggests that semantic representations in autism may be reorganized along different
754 dimensions of meaning, with reduced emphasis on contextual prediction and greater separation
755 of perceptually grounded features.

The presence of semantic coding across all patients indicates that core hippocampal neural mechanisms for representing meaning remain present in autistic patients, but may vary in how effectively they support higher-level contextual language processing. Taken together, our findings suggest that semantic information remains encoded in neural populations in autism but is organized differently within the neural state space. Signals related to contextual prediction, such as surprisal, were less separable and associated with lower effective dimensionality and broader weighting of prior words, consistent with reduced influence of contextual priors. In contrast, perceptually grounded semantic features such as word concreteness were in some cases more separable, suggesting that semantic representations in autism may be reorganized to emphasize different dimensions of meaning rather than reflecting a global reduction in semantic coding. Large language models were critical in revealing these differences, providing quantitative representations of contextual meaning and linguistic structure that allowed us to probe how different semantic features are organized within neural population activity and to gain insight into the neural mechanisms underlying language comprehension in autism.

METHODS

Human intracranial neurophysiology

All experiments were performed in the Epilepsy Monitoring Unit (EMU) at Baylor St. Luke's Hospital using standardized approaches (Xiao et al., 2024A and B). Experimental data were recorded from 11 adult patients (5 males and 6 females) undergoing intracranial monitoring for epilepsy. We recorded data from an additional 3 adult patients (2 males, 1 female) who had comorbid epilepsy and autism (**Extended Data Fig. 1**). The hippocampus was not a seizure focus area of any patients included in the study. Single neuron data were recorded from stereotactic (sEEG) probes, specifically AdTech Medical probes in a Behnke-Fried configuration. Each patient had an average of 3 probes terminating in the left and right hippocampus. Electrode locations are verified by co-registered pre-operative MRI and post-operative CT scans. Each probe includes 8 microwires, each with 8 contacts, specifically designed for recording single-neuron activity. Single neuron data were recorded using a 512-channel *Blackrock Microsystems Neuroport* system sampled at 30 kHz. To identify single neuron action potentials, the raw traces were spike sorted using the *Wave_clus* sorting algorithm (Chaure et al., 2018) and then manually evaluated. Noise was removed and each signal was classified as multi or single unit using several criteria: consistent spike waveforms, waveform shape (slope, amplitude, trough-to-peak), and exponentially decaying ISI histogram with no ISI shorter than the refractory period (1 ms). The analyses here used all single and multiunit activity (see **Extended Data Fig. 2**).

Electrode visualization

Electrodes were localized using the software pipeline intracranial Electrode Visualization (iELVis; Groppe et al., 2017) and plotted across patients on an average brain using Reproducible Analysis & Visualization of iEEG (RAVE; Magnotti et al., 2020). For each patient, DICOM images of the preoperative T1 anatomical MRI and the postoperative Stealth CT scans were acquired and converted to NIfTI format (Li et al., 2016). The CT was aligned to MRI space using FSL (Jenkinson et al., 2002). The resulting coregistered CT was loaded into BioImage Suite (version 3.5β1; Joshi et al., 2011) and the electrode contacts were manually localized. Electrodes coordinates were converted to patient native space using iELVis MATLAB functions (Yang et al., 2012) and plotted on the Freesurfer (version 7.4.1) reconstructed brain surface (Dale et al., 1999). Microelectrode coordinates are taken from the first (deepest) macro contact on the Ad-Tech Behnke Fried depth electrodes. RAVE (Magnotti et al., 2020) was used to transform each patient's brain and electrode coordinates into MNI152 average space. The average coordinates were plotted together on a glass brain with the hippocampus segmentation and colored by patient.

Natural language stimuli

Patients with epilepsy listened to three episodes (5- to 13-minutes in duration) taken from *The Moth Radio Hour,* totaling 27 minutes of listening time (4,128 words). The three stories were, "Life Flight", "The Tiniest Bouquet", and "The One Club". In each story, a single speaker tells an autobiographical narrative in front of a live audience. The three selected stories were chosen to be both interesting and linguistically rich. Stories were played continuously through the built-in audio speakers of the patient's hospital television. The audio signal was synchronized to the neural recording system via analog input going directly from the computer playing the audio into the Neural Signal Processor at 30 kHz.

Audio Transcription

After experiments, the audio .wav file was automatically transcribed using Python and Assembly AI, a state-of-the-art AI model to transcribe and understand speech. The transcribed words and corresponding timestamp output from Assembly AI was converted to a TextGrid and then loaded into Praat, a software for speech analysis. The original .wav file was also loaded into Praat and we manually checked the spectrograms and timestamps, correcting each word to ensure the word onset and offset times are accurate. The TextGrid output of corrected words and timestamps from Praat was converted to a .xls and loaded into Matlab and Python for further analysis.

Semantic embedding extraction from language models

1) Word2Vec. We used the pre-trained *fastText Word2Vec* model in MATLAB to extract word embeddings for all words in our dataset (Joulin et al., 2016; Mikolov et al., 2013). This pre-trained model provides 300-dimensional word embedding vectors, trained on millions of words text, to capture semantic relationships between words. Any surname words, such as "Harwood" or proper nouns like "Applebee's" that did not have word embeddings were discarded from the analysis (these were rare in our sample).

2) GPT-2 Large. In an excel file of our transcribed words, each row corresponded to an individual token, including punctuation and sentence terminators such as ".", "?", and "!". We reconstructed sentences by iterating through the file and appending words until encountering a recognized sentence delimiter. This process yielded multi-word segments that more accurately captured natural linguistic boundaries. Any remaining words following the last delimiter were grouped into a final sentence. Notably, punctuation tokens were preserved to maintain contextual fidelity but were tracked carefully to avoid introducing sub-word alignment errors during tokenization.

To extract GPT-2 embeddings, we employed the "gpt2-large" model (Radford et al., 2019) from the Hugging Face Transformers library (Wolf et al., 2020). This version of GPT-2 features a total of 37 layers (1 initial embedding layer plus 36 transformer layers), each producing 1280-dimensional hidden states, with a maximum context length of 1024 tokens. Although GPT-2 supports a 1024-token context window, all embeddings used in this study were computed within individual sentences only - that is, the model's context was reset whenever a sentence-ending delimiter (e.g., ".", "!", "?") was encountered. We extracted hidden states from all 37 layers using a progressive context approach designed to incorporate GPT-2's autoregressive nature. Specifically, for each sentence, we began with an empty context and added words sequentially. After adding each new word, we tokenized the updated text string via GPT-2's Byte Pair Encoding (BPE) tokenizer, ran the token sequence through the model in no-grad (inference-only) mode, and retrieved the hidden states. We then identified the newly appended word's sub-word tokens and averaged their corresponding vectors to obtain a single word-level embedding. Because GPT-2 often splits words into multiple sub-word fragments (otherwise known as "tokens," e.g., "computa" + "tion"), averaging those fragments preserves consistency with the transcript's original word boundaries. The GPT-2 outputs resulted in 1280-dimensional embeddings for each layer.

Firing rate responses to words

We computed the duration for each word in the story and for each non-word in Jabberwocky stimuli. The firing rate of a neuron for each word was the number of spikes occurring during the word with an 80 ms delay after word onset to account for the approximate delay of information to hippocampus. This value was divided by word duration and then multiplied by 1000 to compute spikes per second.

Word Surprisal

We quantified how predictable each word in the story was to a large language model according to previously described methods (Gwilliams et al., 2024; Weissbart and Martin, 2024). For each word, w_i, we maintained a progressive left-to-right transcript and evaluated its predictability under a series of context windows. Specifically, we extracted the last $C \in \{4,8,16,32,64,128,256,512,1024\}$ tokens preceding w_i, fed this context into GPT-2 Large, and obtained the model's predicted probability distribution over the vocabulary for the upcoming word:

$$Surprisal(w_i) = -log\ P(w_i | w_{i-1}, w_{i-2}, \ldots, w_{i-k})$$

Word Concreteness

Concreteness and abstractness values were derived from the Brysbaert, Warriner, and Kuperman (2014) norms, which provide five-point concreteness ratings for approximately 40,000 English lemmas and two-word expressions collected from over 4,000 native English speakers via Amazon Mechanical Turk. These ratings quantify the extent to which each word refers to a perceptible or experience-based concept (e.g., *table*, *dog*) versus an abstract or linguistic concept (e.g., *justice*, *truth*). Each word was rated by around 25 participants on a 1-5 scale so that the most concrete words are assigned the highest score of 5, and the most abstract words are assigned the lowest score of 1. For each word, the average rating (and standard deviation) across all raters was recorded.

To assign values to words in our corpus, we implemented a Python-based extraction pipeline that automatically matched each lexical item to its corresponding concreteness rating. Words were first cleaned for punctuation and contractions, then lemmatized using the Stanford CoreNLP server (Manning et al., 2014) to ensure consistency with the base forms in the concreteness dataset. Each token was queried against the Brysbaert database using a hierarchical approach: exact matching, lemma-based matching, and fuzzy matching when needed. For each match, both concreteness and abstractness values were stored, with abstractness defined as the inverse of concreteness (5 – rating). The resulting scores were merged with the linguistic feature matrix for all transcribed words.

Regressing spike counts on word embeddings, phonemes, and linguistic features

Word embeddings, such as those derived from Word2Vec or similar models, are typically high-dimensional and can exhibit substantial collinearity among dimensions - that is, many of the embedding features are correlated with one another. We first used Principal Component Analysis (`pca`, Matlab 2023b) on the full word embeddings to obtain uncorrelated features that still capture the dominant structure in the embedding space with reduced dimensionality. For each word, we used the first 100 principal components (PC) from Word2Vec or GPT-2 embeddings because they explained at least 60% of the variance of the original embedding vectors.

We modeled the spike count responses of individual neurons using a Poisson Generalized Linear Model (GLM) with a log-link function and ridge (L2) regularization (we confirmed that spike counts for each word follow a Poisson distribution; **Figure 1G and Figure 3A-B**). The model aimed to predict the number of spikes a neuron fired in response to each word (summed spikes across word duration), using the top 100 principal components (PCs) of the word embedding vector, the duration of the word, and the interaction between each PC and the word's duration as predictors (z-scored prior to model fitting). This resulted in a 201-dimensional feature vector for each word: 100 PC values, 1 duration value, and 100 PC×duration interaction terms.

The Poisson GLM assumes that the spike count y_i for word i is drawn from a Poisson distribution with mean λ_i where:

$$y_i \sim \text{Poisson}(\lambda_i)$$
$$\log(\lambda_i) = \beta_0 + x_i^T \beta$$

Where $\lambda_{i,n}$, the expected spike count for word (i) and neuron n (n), is modeled by the linear regression coefficients (β), one for each of the 201 predictors (x_i^T), plus the y-intercept (β_0).

For each neuron, we fit a Poisson ridge regression model using a nested cross-validation framework with 5 contiguous outer folds. Words were partitioned into five sequential test blocks of approximately equal size, such that in each outer fold one contiguous block of words served as the held-out test set and the remaining four blocks were used for training. This blocked outer-fold design was used to reduce temporal leakage arising from autocorrelation across nearby words in the continuous speech stream. Within each outer training set, the optimal regularization strength (α; alpha) was selected using 5-fold inner cross-validation, drawn from a log-spaced range (10^{-3} to 10^{3}), and the value maximizing the mean validation log-likelihood across inner folds was selected. Using the selected α, a Poisson ridge model was then fit to the full outer training set and then evaluated on the held-out test set using several performance metrics, including log-likelihood and adjusted R^2. To assess model complexity, we estimated the effective degrees of freedom (EDF) from the training data and used this to compute an out-of-sample AIC-like metric for the test set (**Figure 1J**). Final summary statistics for each neuron were obtained by taking the median across the 5 outer folds.

To assess statistical significance relative to a null, we generated 100 shuffled predictor matrices per dataset, in which embeddings were shuffled while keeping word duration preserved. Each shuffle circularly shifted the embedding matrix along the observation axis by a randomly selected offset of at least ±100 samples (to avoid short-range autocorrelation artifacts). To determine if the actual model showed significant improvement from the shuffled, we performed a permutation test comparing the actual model LLH to the shuffled model LLH distribution. We then took the difference between the actual and shuffled model (mean) LLH (LLH diff; ΔLLH). A neuron was fit by the model if its ΔLLH was both positive and significant and if McFadden's pseudo R^2 value was positive ($P < 0.05$, permutation test, **Figure 1H**).

Predictor significance was assessed using p-values from a Poisson generalized linear model fit to the same predictors, while coefficient magnitudes were taken from the L2-regularized Poisson regression model used for prediction. As expected, word duration was always a significant predictor, followed by the first eight embedding dimensions and their interactions with duration, with the number of significant predictors gradually decreasing across higher dimensions.

Phonetic regression. We built a fixed-length feature space over the 43 IPA phonemes observed in our corpus. Here, IPA refers to the International Phonetic Alphabet, a standardized set of symbols that denote speech sounds independent of spelling. The podcast transcript was processed word by word: tokens were lower-cased and converted from graphemes to phonemes using the Python phonemizer package (version 3.0.1) with the eSpeak backend as the grapheme-to-phoneme (G2P) model (https://pypi.org/project/phonemizer/3.0.1/). For each word, we took the canonical IPA transcription returned by phonemizer. Phonemes were then manually inspected and corrected by linguists (JB and HZ) in Praat.

Each word was then represented as a 43-dimensional count vector whose entries reflect the number of occurrences of each IPA phoneme in that word (unigram counts; no duration or stress information). This approach is similar to Khanna et al., in that words are represented by the presence of their constituent phonemes; however, we did not group phonemes into broader classes, in order to preserve the full identity of the 43 phones observed in our data and maintain the embedding's informational richness and dimensionality (Khanna et al., 2024). To better differentiate words that contain the same phoneme set but in different orders (e.g., dog vs god), we double-counted the first phoneme in every word while counting all subsequent phonemes once. The resulting word-by-phoneme matrix (N words × 43 features) was used in subsequent analyses relating phonetic composition to neural responses. We used this word-by-phoneme matrix, word duration, and their interactions in the same Poisson regression described above for predicting spike counts of the current word. The data folds used for training and testing were preserved across semantic and phonetic models and both models had the same number of words.

We used the same Poisson ridge regression model to predict an individual neuron's spike count for each word from 61 linguistic features: (1) full phonetic embeddings (43 IPA phones; count coded, cf. Khanna et al., 2024), (2) 10 PCs of semantic embeddings, (3) word order in sentence, (4) word order in clause (Stanford CoreNLP; Manning et al., 2014), (5) opening node number (Stanford CoreNLP; Manning et al., 2014), (6) closing node number (Stanford CoreNLP; Manning et al., 2014), (7) word frequency (SUBTLEX-US; Brysbaert & New, 2009), (8) pitch, (9) a scalar representing degree of polysemy (Cruse et al., 1986; Landauer, 2001; Ethayarajh, 2019) and (10) word duration (**Extended Data Figs. 3-4**).

Embedding distance

The semantic embedding vector for each word was its full vector of embedding values extracted from GPT-2 layer 25 (1280 in length) language model. For each patient, for each word, its neural embedding vector was every neuron's firing rate response for that word (11- 54 neurons in length). We used the function `pdist`, Matlab 2023b, to compute cosine distance between semantic embedding vectors of all 8,514,001 word pairs, known as semantic distance. We repeated the procedure, computing cosine distance between neural embedding vectors for all word pairs, termed neural cosine distance. "All word pairs" included pairs of the same word. We correlated semantic distance and neural distance from all word pairs to compute the correlation coefficients in **Figure 2B**.

$$\text{Cosine distance } (w_1, w_2) = 1 - \frac{W1 * W2}{||W1||\ ||W2||}$$

Cosine distance between neural or semantic embeddings of word 1 and word 2 is the 1 minus the dot product of embedding vectors for each word, divided by the magnitudes (norms) of each word vector.

Polysemy

To compute polysemy for each word, we computed cosine distance between each GPT-2 layer 25 embedding vector of all occurrences of a given word (at least 2 occurrences, 396 words total). We took the median of this distribution to obtain one polysemy value per word. We repeated the polysemy analysis using neural embeddings instead of GPT-2 embeddings to compute neural cosine distance values. We also computed polysemy for each word as the total number of synsets (i.e., distinct senses) associated with each word in WordNet (Fellbaum, 1998). These polysemy values yielded the same results shown in **Figure 2D.**

Attention Pattern Grid

The ***empirical attention pattern grid*** is an estimate of the degree to which all past words influence each current word in terms of the proportion of influence they have on the semantics of that word (Katlowitz et al., 2025). It therefore recapitulates the function performed by the APG used in transformer architecture LLMs. We first estimated the neural APG from neural data alone and, for comparison, performed an analogous process on the LLM embeddings. Note that the LLM-derived empirical APGs were not derived directly from the LLM APGs themselves; they were inferred so as to keep the estimation procedure the same for brain and LLM. For reference, a true APG from an LLM is the result of the dot product of the Query and Key matrices, and there are many heads of attention per layer.

Our empirical APGs were calculated in the same manner for all embedding matrices. Embedding matrices were 4,128 rows, corresponding to the number of words in our stimulus set, by M columns, corresponding to the number of embedding dimensions per word. For the neural embedding matrix M was equal to the number of neurons per patient (mean 30). For the semantic empirical APGs, M was 1,280 (GPT-2, all layers; **Figure 2E-K**).

We then created two new embedding vectors for each word: the average vector across all instances of that word $\underline{v_i}$ and the shifted representation of the word j is $\Delta v_j = v_j - \underline{v_j}$. Then each value of the APG was created by measuring the cosine similarity between the shifted vector and the mean vector of the previous words

$$APG(i,j) = (\underline{v_i} \cdot \Delta v_j) \,/\, (||\underline{v_i}|| * ||\Delta v_j||)$$

for j=1:4,128 and i=1:j

Words with only one instance in the entire task were excluded from analysis as it was impossible to calculate a shifted representation. Only causal influences were calculated.

Reduced Rank Regression

To quantify how hippocampal population activity predicts high-dimensional semantic embeddings of heard words, we applied Reduced Rank Regression (RRR) using the Matlab code and following the framework of Semedo et al. 2019. For each patient, neurons served as predictors and individual words as observations (**Figure 3C**).

Neural data preprocessing: For each patient, we computed per word firing rates normalized by word duration (see *Firing rate responses to words).* The resulting matrix contained one observation per word and one column per neuron (X). Word-level confounding variables - the log of word frequency and position - were regressed out of the neural activity matrix, and the residuals were used in analysis.

The first 30 Principal Components of semantic embeddings from each layer of GPT-2 were used in the regression, forming a word by semantic embedding matrix (Y). So, a model was fit separately for each GPT-2 layer and patient. RRR estimates a mapping from neural activity X to semantic embeddings Y that is constrained to lie in a low-dimensional shared subspace. We used the Semedo et al., 2019, `ReducedRankRegress` function, which implements the closed-form solution for:

$$Y = XB+\epsilon \qquad B = B_{OLS}V_rV_r^{\top}$$

where V_r are the top r eigenvectors defining the predictive subspace of the OLS mapping. The regression coefficient matrix B is constrained to rank r. For each patient, this decomposition yields:

B_: the ranked predictive components

V: the eigenvectors describing predictive dimensions

These define the semantic subspace captured by the neural population. To determine the number of predictive dimensions, we evaluated models with 0–15 RRR dimensions using 10-fold cross-validation, following Semedo et al. Model performance (averages across folds) was quantified as the cross-validated variance explained (1 – NSE) across predictive subspace dimensionalities (ranks = 0 - 15). The optimal dimensionality (r; rank) can be defined as the number of dimensions needed for the prediction accuracy to plateau, selected using the Semedo et al., 2019 function, `ModelSelect`. These RRR results quantify how many dimensions of semantic variation can be linearly predicted from hippocampal population activity, as well as the geometry of the neural to semantic mapping.

Effective dimensionality. We quantified the effective dimensionality of the semantic-predictive subspace using the participation ratio of the singular-value spectrum of the top r predictive dimensions B_(:,1:r). Effective dimensionality measures how evenly predictive variance is spread across the latent dimensions (ranks). Using each patient's optimal rank or the median optimal rank of control patients when computing effective dimensionality at each layer yielded the same results (**Figure 3G**).

Support Vector Machine Decoder

We used a SVM decoder (Bishop, 2006) with a linear kernel to determine whether firing rates during words carry information about word surprisal by distinguishing the least and most surprising words (**Figure 4D**). For each patient, we used the firing rate responses from every neuron (n = 11-54 neurons per patient) for the most surprising (class 1) and least surprising (class 2) words to predict the class for each word from these neural data. There were 204 words in each class. To train and test the model, we used a tenfold cross-validation. In brief, the data were split into ten subsets, and in each iteration the training consisted of a different 90% subset of the data; the testing was done with the remaining 10% of the data. We used the default hyperparameters as defined in `fitcsvm`, MATLAB 2023b, and z-scored normalization of firing rates. Decoder performance was calculated as the percentage of correctly classified test trials. We compared model performance for predicting train and test data to check for overfitting. In each iteration, we trained a separate decoder with randomly shuffled class labels. The performance of the shuffled decoder was used as a null hypothesis for the statistical test of decoder performance. We

repeated the same procedure above for decoding word concreteness from population activity in each patient (**Figure 4G**). There were 124 words in the most abstract and concrete class.

Canonical Correlation Analysis

To quantify the shared linear structure between neural population activity and linguistic features, we performed canonical correlation analysis (CCA) using the `canoncorr` function in Matlab 2023b. For each patient, neural data consisted of a word-by-neuron firing rate matrix X (words × neurons). Linguistic features were represented as a word-by-feature matrix Y (words × 13 features), including a minimum 10 principal components of GPT-2 semantic embeddings, word surprisal, concreteness, and polysemy. Matrices X and Y were z-scored. CCA finds linear projections of the neural and linguistic feature spaces that maximize their correlation. Specifically, CCA identifies projection matrices *A* and *B* such that:

$$U = XA, \quad V = YB$$

where *U* and *V* are the neural and linguistic canonical scores, respectively. The first pair of canonical variables corresponds to the projections that maximize the correlation between *U* and *V*. We implemented a 10-fold outer cross-validation procedure to estimate out-of-sample canonical correlations. Words were partitioned into 10 contiguous folds. For each fold, CCA weights were learned on the training set and neural and linguistic data from the held-out fold were projected onto the first pair of canonical axes. We then computed the Pearson correlation between held-out neural and linguistic canonical scores (r1). To assess whether observed canonical correlations exceeded chance levels, we constructed a permutation-based null distribution. For each of 1,000 permutations, word labels of the linguistic feature matrix were randomly shuffled and the identical 10-fold cross-validation procedure was repeated using the permuted feature matrix. Then we computed the mean cross-validated canonical correlation for the shuffled model, rPerm. For each patient, we computed the permutation p-value as the proportion of rPerm values greater than or equal to the observed cross-validated r1 (**Figure 5A-B**). We then fit CCA to the full dataset to obtain canonical weights and loadings for interpretation.

Comparison of canonical feature-weight vectors across patients. From the model fit on the full data, we obtained the feature-side canonical weight vector for the first canonical component. Because canonical axes are defined up to a sign flip, we performed sign alignment prior to comparing weights across patients. Specifically, we selected a seed control patient and flipped the sign of each control weight vector when its dot product with the seed was negative. We then computed the mean control direction from these aligned control vectors and used this mean direction as a reference to sign-align all patients (controls and ASD) by flipping any vector with a negative dot product relative to the reference. To compare feature-weighting patterns independent of scale, aligned weight vectors were normalized to unit length. Similarity between patients was quantified using the angular distance between unit vectors, expressed in degrees. Significance of ASD deviations was assessed using a bootstrap null distribution constructed by resampling control patients and computing typical control–control angular deviations; p-values reflect the probability that the observed ASD angle exceeded this null distribution (**Figure 5C**).

Canonical structure loadings and sign alignment. For each linguistic feature j, the structure loading was defined as the Pearson correlation between the original feature time series and the out-of-fold canonical variate on the linguistic side (V_1^{OOf}), computed across word tokens:

$$\text{Loading}_j = \text{corr}(\text{features}_j, V_1^{OOf})$$

Because canonical variates in CCA are defined only up to an arbitrary sign, loading vectors were sign-aligned to enable meaningful comparisons across patients. First, loading vectors for control patients were aligned to a common orientation by flipping the sign of any individual control loading vector whose dot product with the control-group mean loading vector was negative. The resulting aligned control loadings were then used to define a control reference direction. Loading vectors for autistic pateints were subsequently sign-aligned to this control reference direction using the same dot-product criterion. This procedure preserves the relative pattern and magnitude of feature associations while removing arbitrary sign flips inherent to CCA. For control patients, group-level summaries were computed using the median structure loading across patients for each feature, with uncertainty estimated by bootstrap resampling across control patients (**Figure 5D-G**).

Statistics

To assess statistical significance while accounting for differences in neuron counts and small patient sample sizes, we used nonparametric randomization and permutation tests appropriate to the structure of each analysis. For single-neuron analyses (**Figure 1**), significance between control and autistic patients was assessed using a randomization test. For each autistic patient, the observed statistic (e.g., median firing rate or median LLH) was compared to a null distribution generated from 5,000 neuron-count–matched subsamples of control neurons (sampling without replacement within each subsample). P-values were computed as the fraction of null medians at least as extreme as the observed value.

Permutation tests (**Figure 3**): To assess whether a value differed between autistic and control patients, we performed a nonparametric permutation test at the patient level. For each autistic patient, we first computed the observed test statistic as the median across GPT-2 layers of the difference between that patient's value and the control group median at each corresponding layer. To construct a null distribution reflecting typical between-subject variability among controls, we repeatedly (10,000 iterations) selected one control patient at random to serve as a "pseudo-ASD" subject, with the remaining controls forming the reference group. For each iteration, we computed the same median difference statistic between the pseudo-ASD patient and the median of the remaining controls. This procedure generated a null distribution of control-versus-control differences under the assumption of no group effect. Statistical significance was assessed using a one-sided test, quantifying the proportion of null statistics less than or equal to the observed statistic (testing whether autistic patients exhibited lower values than controls).

Decoding accuracy (**Figure 4D and G**): We performed a nonparametric permutation test on group mean accuracy. Under the null hypothesis that group labels were exchangeable, patient labels were randomly permuted (10,000 iterations), assigning three patients to the ASD group and the remaining patients to the control group on each iteration. For each permutation, the test statistic was computed as the difference in mean accuracy between the ASD and control groups. The observed group difference was compared to the resulting null distribution to obtain a one-sided p-value, testing the hypothesis that decoding accuracy was different (lower in surprisal and higher in concreteness) in ASD than in controls.

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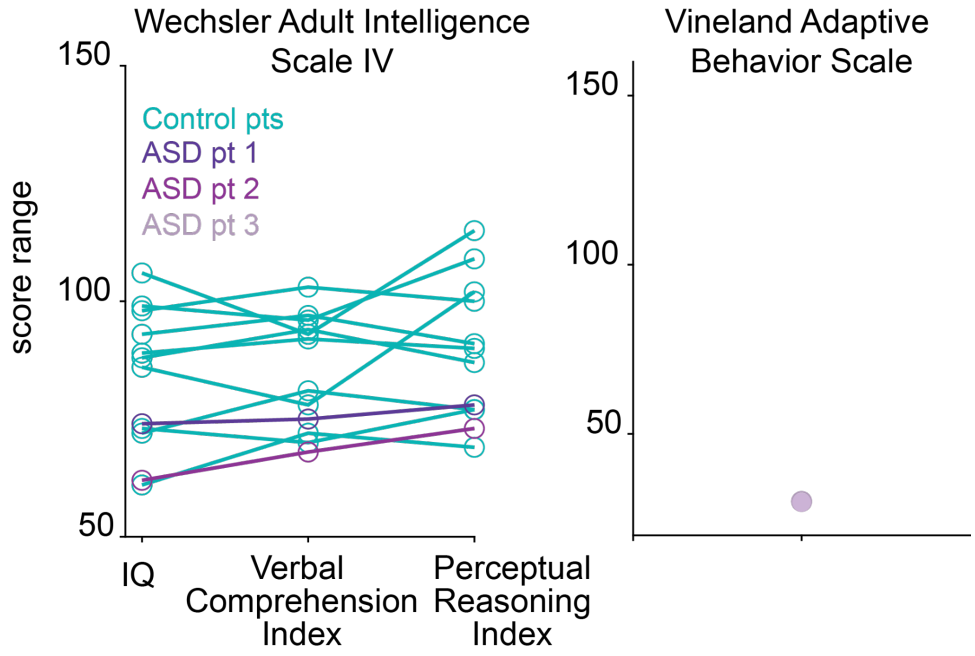
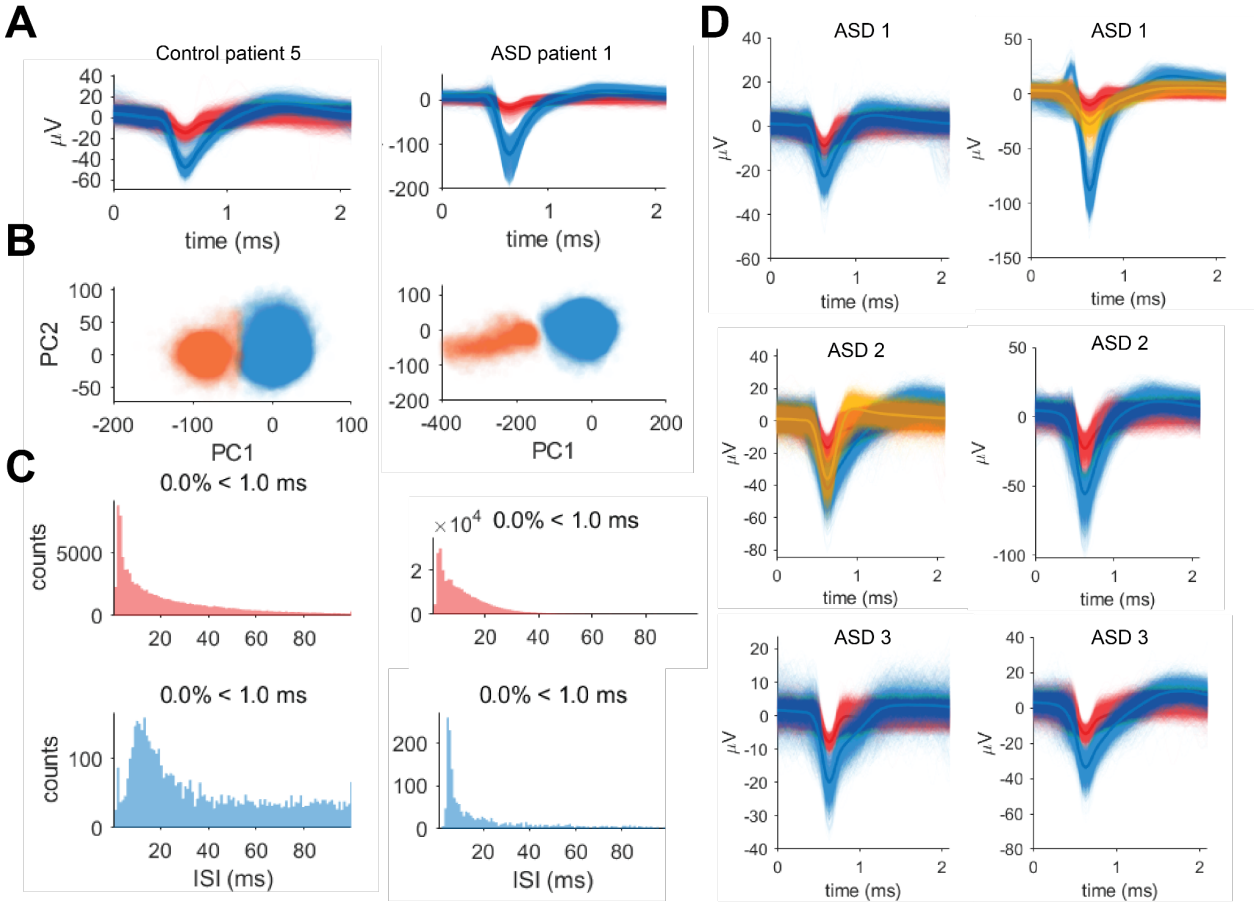
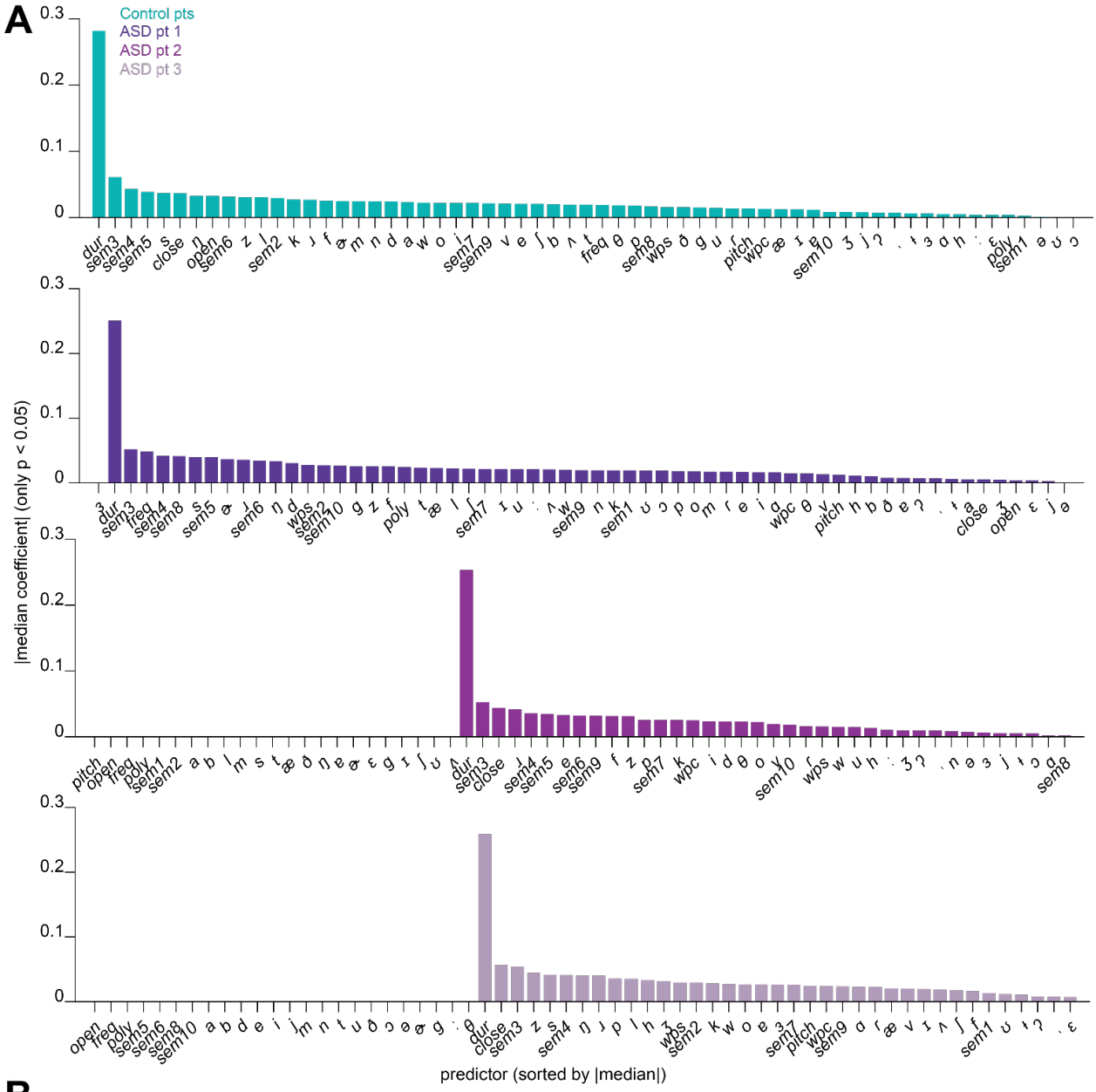
Extended Data Figures

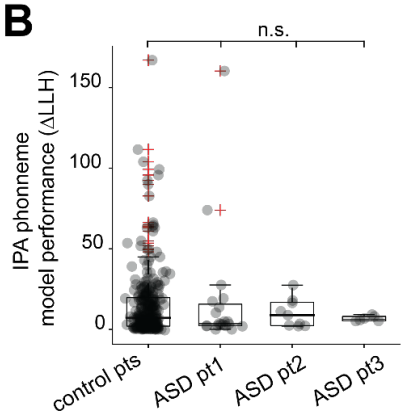


Extended Data Fig. 1 | Test scores from 10 control patients and each ASD patient for cognitive and clinical assessments that were conducted. Assessments were not completed for one control patient.


A
Control patient 5
ASD patient 1
μV
time (ms)
B
PC2
PC1
C
0.0% < 1.0 ms
counts
ISI (ms)
×10^4
D
ASD 1
ASD 2
ASD 3

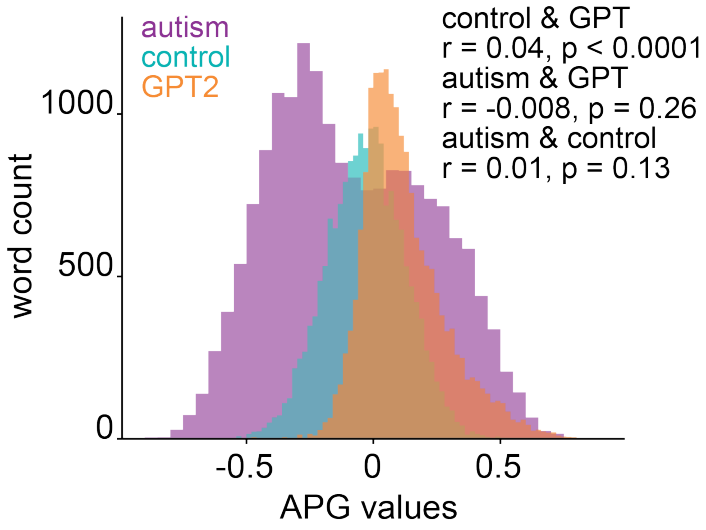
Extended Data Fig. 2 | Single and multi-unit detection and isolation. A, A random sample of 5,000 individual waveforms from a single hippocampal neuron (blue) and multi unit cluster (red) from control patient 5 and ASD1 recorded on one electrode channel. Bolded lines represent average waveforms. Noisy signals were already removed using *Wave_clus* sorting algorithms and manual inspection. **B,** For each patient, all waveforms from each cluster in A are well isolated in Principal Component space. **C,** Interspike interval (ISI) histograms from the neurons in A. Single and multi-unit clusters always have refractory period violations below 5% (as shown in figure titles). **D,** Example hippocampal single (yellow and blue) and multiunit (red) waveforms on individual electrode channels from three autistic patients that were identified and sorted following the criteria in B-C using *Wave_clus* software and manual inspection.


A
Control pts
ASD pt 1
ASD pt 2
ASD pt 3
|median coefficient| (only p < 0.05)
predictor (sorted by |median|)


B
n.s.
IPA phonneme
model performance (ΔLLH)
control pts
ASD pt1
ASD pt2
ASD pt3

Extended Data Fig. 3 | Phonemic and combined linguistic feature regression models. A, The absolute value of the coefficient, or weight, of each predictor in the model is shown on the y-axis. Bars reflect the median predictor weight taken across neurons fit by the model. Predictors are sorted by decreasing weights. Poly = polysemy; Wps = word position in sentence; wpc = word position in clause; freq = word frequency; open and close represent opening and closing nodes; sem1-10 are semantic embeddings from GPT-2 layer 25. Some predictors were not significant for any neurons in ASD patients 2-3. **B,** Log-likelihood improvements (ΔLLH; model performance) for fitted neurons from Poisson ridge regression predicting neuronal spike counts from word-level IPA phoneme embeddings using the equation in Figure 1G. Autistic patient performance is comparable to controls (P = 0.07, 0.62. and 0.42 for ASD1-3 respectively, one-sided Monte Carlo subsampling test on medians using 5,000 neuron-matched resamples from controls).

Extended Data Fig. 4 | Regressing neuronal activity with multiple linguistic features. The number of neurons for which each predictor was significant in the model is plotted on the y-axis, and the total number of neurons is also displayed on top of the bar plot. This model used semantic embeddings from GPT-2 layer 25. Predictors and values correspond to those in Extended Data Fig. 3A. Some predictors were not significant for any neurons in ASD patients 2-3.



Extended Data Fig. 5 | Neural APG distribution from ASD patient subset. The distribution of APG values taken 5 words before each word from the LLM (GPT2-Layer 26 embeddings), control patients, and ASD patients 2-3. Median APG values were taken across patients in each patient group. Pearson correlations between APG values in each group are shown.