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A systematic review of statistical learning in autism spectrum disorder

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Abstract
Statistical learning, the ability to detect and extract statistical regularities from the environment, has been proposed as a key mechanism underlying language, social, and cognitive development. Numerous studies have examined statistical learning abilities in autistic individuals to test the hypothesis that differences contribute to the behavioral presentation of autism spectrum disorder (ASD). Findings have been inconsistent, with variations in methodology, sensory modality, and participant characteristics complicating the interpretation of results. The current study presents a systematic review of statistical, implicit, and procedural learning studies in autism, considering how statistical learning abilities vary across (a) modality (e.g., auditory versus visual), (b) methodology (e.g., behavioral versus neuroimaging), and (c) task design, and considering the influence of language and cognitive abilities. Results across 37 studies in visual and auditory modalities indicate few behavioral differences in statistical learning abilities (with the exception of slowed reaction times in autism), and that learning may benefit from extended exposure and explicit cues. In contrast, neuroimaging findings reveal substantial variability in the neural mechanisms implicated in these tasks, with evidence suggesting compensatory cognitive processing in some autistic samples. Individual differences in language, cognitive abilities, and autism-related traits strongly influence statistical learning outcomes. Significant gaps remain, particularly in the inclusion of minimally verbal individuals and those with intellectual disabilities. Methodological heterogeneity, skewed gender and sociodemographic sample characteristics, and inconsistent neural findings highlight the need for more standardized approaches in future research. Understanding the mechanisms of statistical learning in autism has critical implications for language and cognitive interventions, emphasizing the importance of individualized support strategies.

Keywords Auditory statistical learning, Visual statistical learning, Procedural learning, Implicit learning, Prediction, Reaction time, Functional MRI, EEG

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Introduction

Autism spectrum disorder (ASD) is characterized by persistent deficits in social-emotional reciprocity and the presence of restricted and repetitive behaviors and interests (RRBIs; [1]). Differences in the ability to utilize reliable temporal relationships between events to inform future learning and behavior—known as prediction—have been proposed as a significant contributor to the autistic phenotype [2]; this hypothesis is referred to as *predictive impairment in autism* (PIA). However, "prediction" is a broad construct encompassing multiple cognitive processes; it is often conflated with broader forms of learning, termed statistical learning. Statistical learning represents the implicit, cognitive process of extracting and learning patterns from the environment, which in turn enables prediction to occur.

The current study presents a systematic review of statistical, implicit, and procedural learning studies in autism, examining how statistical learning abilities in autistic individuals vary across (a) modality (e.g., auditory versus visual), (b) methodology (e.g., behavioral versus neuroimaging), and (c) task design. In addition, we review how participant characteristics, including language and cognitive abilities, are reported and controlled across studies.

Prediction in autism

Prediction involves drawing on prior experiences to forecast future events. Our predictive abilities are shaped by two key parameters [2]: [1] strength, which captures the frequency with which Event A precedes Event B (i.e., Markov system transitional probability), and [2] temporal separation, which describes the lag between Events A and B. The predictive value of Event A becomes clearer when probabilities are stronger (e.g., Event A always precedes B) and temporal separations are shorter. Impairments in detecting and encoding probabilistic relationships could lead individuals to require more explicit and repeated exposure to events before forming accurate predictions.

Previous behavioral studies have examined how prediction abilities relate to social behaviors in the general population, including gaze patterns [3], dyadic interactions [4–9], smile reciprocity [10], and broader measures of social engagement [11–13]. However, these studies primarily focus on the use of prediction—forecasting future events—rather than the learning of probabilistic relationships that make prediction possible. This distinction underscores the importance of investigating the learning mechanisms that support prediction, such as statistical learning.

Statistical learning

Engaging in prediction necessarily relies on a learning mechanism capable of acquiring knowledge about probabilistic relationships between environmental events. Statistical learning reflects this implicit ability to detect regularities, extract relevant information, and update expectations accordingly. This process has been extensively investigated across cognitive domains. For example, typical language learning requires tracking environmental regularities to scaffold linguistic development: infants discern native phonemes and words, map words to objects and events, organize words into syntactic structures, and eventually form multi-word utterances [14, 15]. In classic work by Saffran, Aslin, and Newport (1996), 8-month-old infants successfully learned statistical regularities of an artificial language after only two minutes of exposure. Since then, statistical learning has been studied in numerous cognitive processes in both neurotypical (NT) individuals and those with developmental disorders (e.g., developmental language disorder;) [16, 17].

Given this foundation, statistical learning difficulties could plausibly contribute to language impairments in autism. Although no longer part of the core diagnostic criteria, many individuals with ASD experience substantial receptive and expressive language challenges [18]. Pragmatic language difficulties are common, and many also struggle with structural aspects of language such as morphosyntax [19]. Estimates suggest that roughly 50% of verbal autistic individuals show structural language impairment [18, 20, 21], and as many as 30% of all autistic individuals remain minimally verbal [22–25]. We hypothesize that the heterogeneous language profiles observed in autism may, in some individuals, stem from difficulties with statistical learning [26].

Methodological heterogeneity

Research on implicit pattern learning in autism has been described using several overlapping terms—statistical, implicit, probabilistic, and procedural learning—each emphasizing different aspects of similar underlying mechanisms. Distinct terminologies, theoretical frameworks, and methodological approaches appear across separate literatures, often with limited crosstalk [27, 28]. Moreover, studies of infants typically employ a statistical learning framework, whereas implicit and procedural learning paradigms are more common in studies of older children and adults. Given the conceptual overlap and lack of sharply defined theoretical distinctions, the present review integrates these literatures to examine statistical learning writ large.

In statistical learning studies, participants track statistical information embedded in their environment and incorporate this information into priors for future learning. Such studies may use auditory stimuli [29], visual stimuli [30, 31], or both (e.g., cross-situational word learning; [32]). Implicit, probabilistic, and procedural learning studies, meanwhile, employ a range of paradigms, including artificial grammar learning [33], contextual cueing [34], probabilistic classification [35], and serial reaction time tasks [36]; see Table 1 for descriptions. Although these tasks share a common goal—tracking probabilistic relationships—they differ in modality, participant engagement (passive exposure versus active response), and measurement approaches (behavioral, eye-tracking, neuroimaging, etc.). Additional sources of variability include participant matching, stimulus selection, task instructions, and age at testing. Because a detailed account of each study is beyond the scope of this paper, we refer readers to individual reports and to recent comprehensive reviews [37–42].

The current review

Reflecting this experimental variability, as well as the heterogeneity of autism, it is unsurprising that findings in this literature are mixed. Several reviews describe the myriad of findings in neurodevelopmental and language disordered populations [14, 27, 43–45], though none have focused exclusively on autism, nor have they contrasted the impact of modality and methodology differences. In addition, prior reviews did not describe the reporting of cognitive and language abilities of autistic samples, a critical aspect of comparing results and their generalizability.

This pre-registered review (PROSPERO ID CRD42023431728) presents a systematic review of statistical, implicit, and procedural learning studies in autism, considering how statistical learning abilities in autism vary across (a) modality (e.g., auditory versus visual), (b) methodology (e.g., behavioral versus neuroimaging), and (c) task design. In addition, we review the reporting of language and cognitive abilities of participants. We hypothesized that the literature would reflect mixed findings within and between modalities and methodologies, with additional variability introduced between task designs, especially for those with greater task demands. We hypothesized that the neuroimaging literature would be characterized by the most variable findings, because individual differences in neural functioning would be magnified. Finally, we hypothesized that reporting of cognitive abilities would be common (e.g., more than 80% of articles reporting a measure of cognitive abilities), while reporting of language abilities would be infrequent (e.g., less than 20% of articles). We also predicted that most (e.g., greater than 80%) of the articles reporting language and cognitive abilities would describe individuals with cognitive and language abilities in the average range, excluding autistic individuals with greater impairments.

Methods

Search strategy

This review was informed by the Preferred Reporting Items for Systematic Review and Meta-Analyses statement (PRISMA; [38]). Search terms and strategies were developed from early exploratory searches and finalized with the assistance of an academic librarian. Four databases were searched in June 2023 and then again in June

Table 1 Overview of statistical learning paradigms

Task	Modality	Literature	Description
Sequence segmentation	A or V	SL	Participants are exposed to continuous visual or auditory streams whose units (e.g., shapes, syllables, tones) have distinct transitional probabilities. Learning is measured by the ability to discriminate learned versus foil items using 2AFC accuracy, head-turn preference, or fixation duration.
Cross-situational word learning	MM	SL	Participants view novel objects paired with nonword labels across multiple trials, without feedback, such that label–object co-occurrence probabilities differ. Learning is measured by correct identification of word–object pairings via 2AFC or fixation preferences.
Visual scene	V	SL	Participants view visual arrays in which certain object pairs consistently co-occur in specific spatial configurations. Learning is measured by the ability to recognize or choose previously co-occurring object pairs over foil pairs (e.g., in 2AFC tests).
Artificial grammar learning	A or V	SL, IL	Participants are exposed to sequences generated by a hidden grammatical rule and later judge the grammaticality of novel sequences. Learning is measured by above-chance classification of grammatical versus ungrammatical items, reflecting implicit extraction of rule-based regularities.
Contextual cueing	V	IL	Participants search for a target among distractors, with target locations predictably associated with specific distractor configurations. Learning is measured by faster reaction times (RTs) for repeated versus novel spatial configurations, indicating extraction of predictive context–target relationships.
Probabilistic classification	V	IL	Participants categorize stimuli into probabilistic categories based on feedback during training. Learning is measured by increased accuracy and generalization to novel stimuli, reflecting internalization of probabilistic cue–outcome relationships.
Serial reaction time (SRT)	V	SL, IL	Participants respond to stimuli appearing in a repeating sequence by pressing corresponding buttons. Learning is measured by faster RTs for predictable versus random sequences, indicating implicit learning of sequential regularities.

Note: Auditory (A); Visual (V); Multimodal (MM); Statistical learning (SL); Implicit learning (IL); Two-alternative forced choice (2AFC); Reaction time (RT)

2025: PubMed MEDLINE, APA PsycInfo, and Google Scholar. Controlled vocabulary was integrated into the overall search strategy for each database (e.g., Medical Subject Headings; MeSH terms). Search terms covered three broad concepts:

1. [all fields] Statistical Learning OR Statistical-Learning OR Probability Learning OR Experience Dependent Learning OR Experience-Dependent Learning OR Implicit Learning

AND

2. [all fields] Autis* OR ASD OR Asperger's OR PDD-NOS OR Developmental Disorders OR Developmental Disabilities OR Diagnosis Related Groups OR Phenotypes OR Language Development Disorders

NOT

3. [all fields] Machine Learning OR Artificial Intelligence OR Deep Learning

Eligibility

Studies were included if they utilized an auditory or visual statistical learning task: sequence segmentation, cross-situational word learning, visual scene, artificial grammar learning, contextual cueing, probabilistic classification, or serial reaction time. Inclusion criteria were (1) individuals with a clinical diagnosis of autism spectrum disorder (AUT) as a study population; (2) use of a statistical learning task in either the visual and/or auditory modality; (3) empirical measurement of statistical learning performance using behavioral or neuroimaging methods (electroencephalography/event related potentials; EEG/ERP), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), or functional near-infrared spectroscopy (fNIRS); (4) three participants or more per group; (5) includes a non-autistic comparison group; and (6) published in English. Exclusion criteria were (1) measurement of autism characteristics in a sample of non-autistic controls or (2) in siblings of autistic individuals; (3) reliance on rule learning, cognitive flexibility (e.g., the Wisconsin Card Sort Task), or decision-making tasks (e.g., the Iowa Gambling Task); or (4) statistical learning results not reported in analyses.

Selection process and data extraction

Zotero software [47] was used for reference management and to remove duplicate references. Rayyan [48] was used for title, abstract, and keyword screening. Two independent blind reviewers (R.R.C. and H.R.T.) completed the initial title, abstract, and keyword screening. Any conflicting inclusion decisions were discussed until a consensus determination was reached. Full-text articles were retrieved and assessed for eligibility by the first author, and the following data were extracted: participant characteristics (sample size, age, gender, cognitive abilities, language abilities); task design (modality, type of statistical learning task); data collection method (behavioral, neuroimaging type); and main findings. Results were then synthesized in line with the aims of the review: [1] variability of statistical learning performance across modalities, methods, and task designs; [2] representation of language and cognitive abilities of study samples.

Results

Initial searches yielded 351 results after removing duplicates. After screening for title, abstract, and keywords, 70 full-text articles were retrieved and assessed for study eligibility. A final sample of 37 reports met inclusion criteria and were included in this review; see Fig. 1.

Participant characteristics

All study samples were male-biased; five of the 34 (15%) studies included only male participants, and seven studies did not report gender. Participant age ranged from two to 45 years. Consistent with prior research indicating limited reporting of important sociodemographic characteristics [49], only one study [50] reported race/ethnicity and two [51, 52] reported socioeconomic status; participants were predominantly White (85%) with high parental education (M = 15.88 years).

Representation of Cognitive and Language Abilities

All but three studies [51, 53, 54] reported full-scale IQ, verbal abilities, and/or nonverbal abilities; see Table 2. Of the 30 studies that reported full-scale IQ and/or nonverbal abilities (excluding) [43–46], participants in 26 studies (87%) had abilities within the average range. Of the 21 studies that reported language abilities, participants in 16 (76%) had abilities within the average range; participants in five studies [45, 55, 56, 58, 59] had abilities in the below to average range; and two studies [60, 61] reported ranges without numeric standard or scaled scores that ranged from below to above average. Overall, most study samples included individuals with *average* verbal and nonverbal abilities, with moderate representation of individuals with below-average functioning in the language domain.

Study Characteristics

Within the auditory modality, studies utilized word or tone sequence segmentation tasks to probe statistical learning; see Table 3. Within the visual modality, studies utilized object or letter sequence segmentation, contextual cueing, serial reaction time (SRT), probabilistic

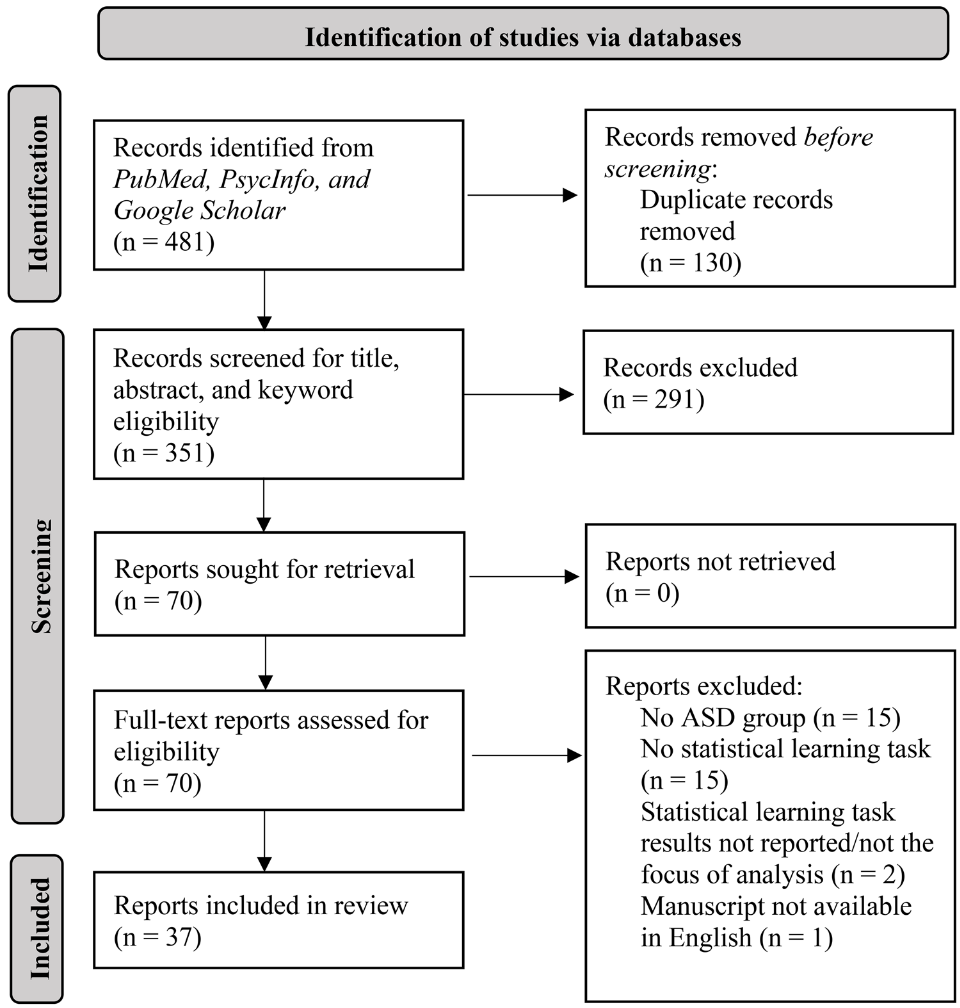

Fig. 1 PRISMA flow diagram

classification, artificial grammar learning, and visual scene paradigms. Finally, studies utilized cross-situational word learning tasks to assess both auditory and visual modalities.

Auditory statistical learning

Behavioral results

Word and tone segmentation A total of two studies [45, 62] examined behavioral word sequence segmentation and one study [59] examined both word and tone sequence segmentation in children and adolescents with and without autism. Haebig et al. (2017) and Mayo and Eigsti (2012) matched on both age and full-scale IQ, whereas Hu et al. (2023) matched on age alone. Neither Haebig et al. (2017) nor Mayo and Eigsti (2012) found group differences in 2AFC accuracy, with both groups performing significantly above chance (i.e., showing learning). In contrast, Hu et al. (2023) found lower accuracy on word segmentation in a sample of 55 speaking children with autism ages 6–12 years, with accuracy (familiarized versus novel syllabic triplets) positively associated with verbal ability. A group by task interaction suggested that group differences were larger for linguistic (letters, syllables) relative to non-linguistic (tones, images) conditions, suggesting a greater impairment in *linguistic* statistical learning in the autism group, particularly in younger autistic participants. Note that the analytic approach employed in Hu et al. (2023) differed from that of the six other studies; in addition to standard accuracy analyses of an offline 2AFC choice, the authors examined RT slope over the course of the 5-minute exposure to each task, as participants completed a target monitoring task. Analyses probed a composite score, calculated as the average of two separate z-scores (RT and accuracy) for each task. The task-specific z-scores were then averaged within domain (linguistic and non-linguistic) to compute a domain-specific z-score. This analytic approach somewhat reduces comparability of this with the other studies employing similar paradigms. In addition, participants completed four different SL tasks within a single sitting; while the order of tasks was counterbal-

Table 2 Characteristics and findings of studies included in this review

Reference	Modality	Method	Task design	*N* (Female) AUT, NT	Age (years) M(SD) AUT, NT	FSIQ M(SD) AUT, NT	Nonverbal IQ M(SD) AUT, NT	Verbal IQ M(SD) AUT, NT	Main findings
Barnes et al., 2008	**Visual**	**Behav**	Contextual cueing and SRT	14 (1 F) 14 (1 F)	11.6 (1.7) 11.0 (1.8)	110.4 (12.6)[a] 116.3 (13.8)[a]	DNR	DNR	Compared to NT, AUT had slower RT for contextual cueing but not SRT. AUT RT increased with practice for repeated or patterned stimuli in both tasks. AUT showed larger magnitude of learning on SRT; no group differences on learning in contextual cueing.
Bo et al., 2022	**Visual**	**Behav**	SRT	12 (3 F) 16 (4 F)	7.8 (2.1) 7.8 (2.0)	DNR	DNR	34–130[**] DNR	No group differences in RT during learning. NT showed greater RT decrease from baseline in immediate and delayed test trials. Across groups, faster RT correlated with learning and motor abilities; no relationship for slower RT.
Brown et al., 2010	**Visual**	**Behav**	Contextual cueing, SRT, Artificial grammar, probabilistic classification	31 (3 F) 31 (3 F)	11.6 (1.1) 11.7 (1.5)	99.6 (19.2)[a] 107.8 (11.5)[a]	99.5 (18.9)[a] 107.0 (12.3)[a]	99.7 (18.5)[a] 106.9 (11.6)[a]	No group differences in task learning. Contextual cueing and SRT: AUT > NT RT, but greater decrease in RT over time indicating greater benefit from practice.
D'Cruz et al., 2009	**Visual**	**Behav**	SRT	52 (5 F) 54 (5 F)	19.6 (11.3) 20.3 (12.2)	108.0 (16.8)[a] 110.5 (15.4)[a]	DNR	DNR	AUT RT decreased across learning and for high compared to low probability trials; no group differences. Rightward, but not leftward saccades faster with learning for AUT compared to NT.
Gordon and Stark, 2007	**Visual**	**Behav**	SRT	7 (0 F) 9 (0 F)	10.9 (DNR) 12.3 (DNR)	Below avg[*] DNR	DNR	Below avg[*] DNR	AUT increased accuracy and decreased RT over learning trials; AUT > NT overall RT, with no evidence of learning at the individual level. When task was simplified, some individuals displayed learning.
Izadi-Najafabadi et al., 2015	**Visual**	**Behav**	SRT	15 (0 F) 16 (0 F)	8.6 (1.4) 8.7 (1.6)	82.9 (18.0)[a] 87.44 (17.1)[a]	DNR	DNR	AUT RT decreased over the course of learning trials; no group differences.
Jiang et al., 2013	**Visual**	**Behav**	Contextual cueing	15 (2 F) 15 (2 F)	10.4 (DNR) 10.8 (DNR)	DNR	106.3 (DNR)[a] 109.0 (DNR)[a]	DNR	AUT: faster RT for high-probability location; no group differences. AUT showed greater reduction in RT with practice.
Jones et al., 2018	**Visual**	**Behav**	Contextual cueing	56 (11 F) 68 (30 F)	5.4 (1.3) 5.0 (1.4)	DNR	106.5 (21.1)[a] 112.1 (18.3)[a]	101.2 (17.4)[a] 112.1 (16.8)[a]	AUT RT decreased for high and low frequency conditions; NT had flat and quadratic RT changes for high and low frequency conditions. In AUT, individuals with lesser autism symptoms had RT trajectory more similar to NT for high but not low frequency conditions. Across groups and conditions, high verbal IQ associated with NT-typical RT trajectory.
Kourkoulou et al., 2012	**Visual**	**Behav**	Contextual cueing	16 (3 F) 17 (6 F)	19.0 (2.3) 19.0 (2.1)	101.0 (11.3)[a] 106.4 (11.9)[a]	104.1 (11.2)[a] 109.4 (11.5)[a]	97.8 (14.5)[a] 102.7 (14.6)[a]	AUT: faster recognition in repeated compared to novel trials, showing benefit from contextual cueing; no group differences. AUT: slower RT, especially for novel trials.
Kourkoulou et al., 2013	**Visual**	**Behav**	Contextual cueing	15 (3 F) 18 (2 F)	19.0 (1.6) 21.0 (4.1)	101.3 (12.4)[a] 102.7 (9.5)[a]	104.2 (12.9)[a] 107.1 (10.3)[a]	98.3 (15.5)[a] 97.6 (9.8)[a]	AUT: faster recognition of repeated compared to novel trials, showing benefit from contextual cueing; no group differences. AUT: slower RT, slower first saccade, and longer fixation duration.

Table 2 (continued)

Reference	Modality	Method	Task design	*N* (Female) AUT, NT	Age (years) M(SD) AUT, NT	FSIQ M(SD) AUT, NT	Nonverbal IQ M(SD) AUT, NT	Verbal IQ M(SD) AUT, NT	Main findings
Mercado et al., 2015	**Visual**	**Behav**	Probabilistic classification	13 (2 F) 13 (2 F)	10.8 (1.6) 10.9 (1.5)	109.2 (11.1)[a] 112.7 (9.2)[a]	107.7 (11.3)[a] 114.6 (9.8)[a]	108.9 (12.3)[a] 108.5 (9.0)[a]	Two learning and generalization patterns in AUT: accurate differentiation of category from non-category members (similar to NT) or chance performance. Across two learning contexts, some AUT had consistent learning and generalization patterns, and others switched. No clear predictors of probability of switching.
Nader et al., 2022	**Visual**	**Behav**	Probabilistic classification	54 (7 F) 52 (16 F)	10.1 (2.0) 10.0 (1.8)	DNR	104.3 (24.9)[a] 111.3 (19.0)[a]	DNR	AUT able to learn and generalize probabilistic categories; no group differences. AUT performance enhanced by simultaneously presented information.
Nemeth et al., 2010	**Visual**	**Behav**	SRT	13 (2 F) IQ-M: 13 (0 F) Age-M: 14 (2 F)	11.8 (3.1) IQ-M: 9.2 (2.6) Age-M: 11.6 (3.3)	93.2 (20.7)[a] IQ-M: 96.5 (17.7)[a] Age-M: 109.1 (12.8)[a]	DNR	DNR	AUT: faster RT, greater accuracy for high vs. low probability events; no group differences. Offline learning improved overall RT and accuracy, but not specific to high probability trials; no group differences.
Ong et al., 2025	**Visual**	**Behav**	Probabilistic classification	52 (20 F) 52 (24 F)	29.1 (6.8) 30.8 (8.0)	DNR	DNR	DNR	Above-chance performance across groups and conditions. No group differences in single-cue probabilistic learning. NT > AUT when weakly predictive associations were weakly predictive; no differences when strongly predictive. AUT learning rate > NT.
Parsons and Baron-Cohen, 2023	**Visual**	**Behav**	Sequence segmentation (object)	61 (17 F) 64 (19 F)	32.2 (8.4) 30.0 (7.8)	115.9 (13.2)[a] 118.5 (10.0)[a]	DNR	DNR	AUT above chance on 2AFC for specific and generalized exemplars given the same type of exemplars during exposure; no group differences. AUT: lower 2AFC accuracy when given specific exemplars and tested on generalized exemplars.
Pesthy et al., 2023	**Visual**	**Behav**	SRT	22 (4 F) 20 (6 F)	27.3 (7.3) 25.4 (6.2)	DNR	DNR	DNR	AUT and NT = similar RT and accuracy, similar temporal dynamics of learning.
Pultsina et al., 2024	**Visual**	**Behav**	Probabilistic classification	23 (18 F) 23 (18 F)	29.2 (6.9) 28.2 (6.0)	104.6 (8.9) 106.8 (7.0)	DNR	DNR	AUT and NT participants learned probabilistic choices in terms of choice ratio (accuracy) and RT. Learning probabilities increased pupillary arousal for AUT group vs. decreased arousal for NT group. Greater arousal during choice task correlated with greater degree of self-reported intolerance for uncertainty in daily life.
Roser et al., 2015	**Visual**	**Behav**	Visual scene	Children 28 (4 F) 22 (12 F) Adults 10 (4 F) 10 (6 F)	Children 13.0 (1.6) 13.0 (1.6) Adults M: 37.0 (DNR) F: 45.0 (DNR) M: 41.0 (DNR) F: 32.0 (DNR)	Children DNR Adults M: 117.0 (DNR)[a] F: 113.0 (DNR)[a] M: 123.0 (DNR)[a] F: 117.0 (DNR)[a]	DNR	DNR	AUT adults: greater 2AFC accuracy; no group differences for children.

Table 2 (continued)

Reference	Modality	Method	Task design	*N* (Female) AUT, NT	Age (years) M(SD) AUT, NT	FSIQ M(SD) AUT, NT	Nonverbal IQ M(SD) AUT, NT	Verbal IQ M(SD) AUT, NT	Main findings
Shuwerk et al., 2016	**Visual**	**Behav**	Contextual cueing	Children 26 (DNR) 24 (DNR) Adults 18 (DNR) 17 (DNR)	Children 9.7 (1.9) 9.7 (1.9) Adults 37.1 (11.5) 35.9 (14.1)	DNR	Children 105.4 (16.1)[a] 110.1 (15.9)[a] Adults 108.1 (21.4)[a] 109.1 (16.1)[a]	Children 111.6 (14.9)[a] 106.3 (11.6)[a] Adults 114.1 (14.7)[a] 118.4 (16.1)[a]	No enhancement to performance in AUT after exposure to repeated trials.
Solomon et al., 2011	**Visual**	**Behav**	Probabilistic classification	28 (5 F) 30 (5 F)	23.5 (5.5) 24.4 (5.1)	111.0 (16.0)[a] 115.8 (13.0)[a]	108.6 (16.4)[a] 112.3 (12.8)[a]	110.7 (15.6)[a] 112.8 (11.3)[a]	In early learning, AUT better than NT in identifying low-probability pairs; no group differences on high- and mid-probability. No differences in accuracy after training.
Travers et al., 2010	**Visual**	**Behav**	SRT	15 (DNR) 18 (DNR)	19.0 (2.9) 19 (2.1)	103.0 (17.8)[a] 100.0 (14.1)[a]	106.0 (14.4)[a] 99.0 (12.0)[a]	99.0 (19.1)[a] 100.0 (15.3)[a]	AUT RT decreased across learning trials and for high compared to low probability trials; no group differences. AUT RT slower.
Travers et al., 2013	**Visual**	**Behav**	Contextual cueing	16 (0 F) 20 (0 F)	18.7 (3.2) 19.4 (2.6)	101.7 (18.0)[a] 101.8 (17.2)[a]	105.3 (14.0)[a] 101.1 (13.2)[a]	97.4 (19.9)[a] 102.0 (19.1)[a]	No group differences in learning rate; AUT RT slower. Global and local contextual cueing facilitated learning for both groups; global-only contextual cueing facilitated learning for NT but not AUT.
Virág et al., 2017	**Visual**	**Behav**	SRT	14 (DNR) 14 (DNR)	11.0 (3.1) 12.0 (2.7)	105.8 (27.8)[a] 108.6 (17.7)[a]	DNR	DNR	AUT more accurate than NT for non-cued sequences; no group differences on cued sequences. No group differences in retention after delay.
Zwart, Vissers, and Maes, 2018	**Visual**	**Behav**	SRT	Study 1 19 (5 F) 19 (12 F) Study 2 16 (2 F) 18 (4 F)	Study 1 38.0 (DNR) 31.1 (DNR) Study 2 23.3 (DNR) 22.8 (DNR)	Study 1 111 (DNR)[a] 109 (DNR)[a] Study 2 107 (DNR)[a] 114 (DNR)[a]	DNR	DNR	No group RT differences for probabilistic or deterministic sequences. AUT severity positively correlated with RT for deterministic but not probabilistic sequence learning.
Mayo and Eigsti, 2012	**Auditory**	**Behav**	Sequence segmentation (word)	17 (3 F) 24 (9 F)	13.1 (2.9) 13.0 (2.6)	103.0 (11.5)[a] 105.0 (11.5)[a]	11.1 (3.1)[b] 11.0 (2.4)[b]	110.4 (13.7)[a] 115.9 (10.8)[a]	AUT above chance 2AFC; no group differences. Less differentiation in accuracy between high and low transitional probabilities compared to NT.
Hu et al., 2023	**Auditory and Visual**	**Behav**	Sequence segmentation (word, letter, tone, and object)	55 (10 F) 50 (28 F)	8.3 (1.2) 8.6 (1.9)	DNR	DNR	80.5 (23.8)[a] 110.1 (13.7)[a]	AUT: worse performance on word and letter segmentation; more evident in younger vs. older AUT. Correlation between linguistic SL performance and verbal abilities. No group differences on nonlinguistic tone and object sequence segmentation.

Table 2 (continued)

Reference	Modality	Method	Task design	*N* (Female) AUT, NT	Age (years) M(SD) AUT, NT	FSIQ M(SD) AUT, NT	Nonverbal IQ M(SD) AUT, NT	Verbal IQ M(SD) AUT, NT	Main findings
Haebig et al., 2017	**Auditory and Multi-modal**	**Behav**	Sequence segmentation (word), cross-situational word learning	25 (3 F) 26 (13 F) 23 (12 F)[c]	10.1 (1.4) 10.4 (1.3) 10.3 (1.2)	DNR	103.7 (16.6)[a] 104.5 (9.1)[a] 102.4 (10.9)[a]	88.4 (20.2)[a] 103.7 (12.4)[a] 81.9 (14.2)[a]	No differences in word segmentation or word-object mapping performance. AUT: stronger language associated with more looking to target during word-object mapping; no relationship between language and word segmentation.
Venker, 2019	**Multi-modal**	**Behav**	Cross-situational word learning	18 (0 F) 21(6 F)	6.3 (1.4) 4.8 (1.8)	95.0 (19.0)[a] 120.0 (13.0)[a]	DNR	94.0 (20.0)[a] 120.0 (10.0)[a]	AUT above chance on word learning task; no group differences. Familiar word recognition correlated with cross-situational word learning.
Hasenstab et al., 2016	**Visual**	**EEG**	Sequence segmentation (object)	34 (DNR) 32 (DNR)	Range: 2–5	DNR	DNR	DNR	AUT positive mean differentiation of P3 amplitude for learned vs. novel stimuli; NT negative mean differentiation. Some AUT showed flat differentiation; some NT showed positive differentiation; no AUT showed negative differentiation.
Jeste et al., 2015	**Visual**	**EEG**	Sequence segmentation (object)	68 (DNR) 35 (DNR)	4.5 (1.1) 4.5 (1.0)	77.7 (24.3)[a] 117.1 (11.8)[a]	81.8 (24.0)[a] 110.0 (10.9)[a]	80.6 (23.5)[a] 116.3 (11.9)[a]	Greater N1 responsivity to expected vs. unexpected events in NT but not AUT. Positive relationship between N1 amplitude and NVIQ, and P300 amplitude and social functioning in AUT; high NVIQ and social functioning AUT (high-AUT) had significantly different N1 and P300 activity compared to low NVIQ and social functioning AUT (low-AUT) and NT; no group differences between low-AUT and NT.
Travers et al., 2015	**Visual**	**fMRI**	SRT	15 (0 F) 15 (0 F)	20.8 (4.0) 21.4 (2.9)	109.5 (16.9)[a] 112.7 (8.4)[a]	110.2 (13.4)[a] 108.2 (10.3)[a]	106.7 (18.4)[a] 114.3 (7.7)[a]	AUT RT decreased across learning trials and for high compared to low probability trials, but less than NT. AUT: decreased activation of right parietal lobule and right precuneus during learning. Activation correlated with RT difference between high and low probability trials and negatively correlated with severity of RRBI.
Zwart et al., 2017	**Visual**	**EEG**	SRT	20 (DNR) 20 (DNR)	38.3 (12.7) 30.5 (12.7)	111.0 (9.9)[a] 109.4 (12.8)[a]	DNR	DNR	Frontal P3 but not fronto-central N2b enhancement for deviant trials in AUT compared to NT. Behavioral RT faster for learned than deviant sequences in AUT; no group differences.
Zwart, Vissers, Kessels, and Maes, 2018	**Visual**	**EEG**	SRT	16 (7 F) 17 (8 F) 13 (9 F)[c]	11.3 (0.9) 11.2 (0.8) 11.3 (0.6)	96.6 (13.5)[a] 105.4 (13.4)[a] 99.9 (10.4)[a]	DNR	DNR	AUT central N2b, but not frontal P3, enhancement in early and late stages of task, only for early stages in NT and not at all in SLI. Behavioral RT faster for learned than deviant sequences in AUT; no group differences.
Arnett et al., 2018	**Auditory**	**EEG**	Sequence segmentation (word)	76 (15 F) 27 (10 F)	12.1 (2.9) 13.0 (2.3)	DNR	88.5 (28.6)[a] 113.6 (16.0)[a]	88.5 (28.6)[a] 113.6 (16.0)[a]	No group differences in P1 amplitude or latency. Higher receptive language abilities related to attenuated P1 amplitude for learned vs. novel words in AUT only.
Li et al., 2020	**Auditory**	**EEG**	Sequence segmentation (word)	32 (DNR) 9 (DNR)	Range: 4–12	DNR	DNR	Verbal-minimally verbal* DNR	No group differences in alpha power for verbal groups; lower power in minimally verbal AUT. No group differences in gamma power between verbal and minimally verbal AUT; NT had higher power. Across groups, verbal abilities correlated with alpha across regions and gamma in temporal regions; gamma negatively correlated with verbal abilities in right frontal regions. Age correlated with gamma but not alpha.

Table 2 (continued)

Reference	Modality	Method	Task design	*N* (Female) AUT, NT	Age (years) M(SD) AUT, NT	FSIQ M(SD) AUT, NT	Nonverbal IQ M(SD) AUT, NT	Verbal IQ M(SD) AUT, NT	Main findings
Scott-Van Zeeland et al., 2010	**Auditory**	**fMRI**	Sequence segmentation (word)	24 (0 F) 24 (0 F)	12.6 (2.5) 11.6 (1.6)	102.2 (19.8)[a] 104.0 (12.4)[a]	DNR	96.1 (17.9)[a] 102.8 (12.9)[a]	Fronto-temporal-parietal network activity decreased as number of cues to word boundaries increased for NT but not AUT. Signal increased over time in basal ganglia and left tempo-parietal cortex for NT but not AUT; severity of language impairment inversely correlated with signal increases in AUT.
Wagley et al., 2020	**Auditory**	**MEG**	Sequence segmentation (word)	15 (1 F) 14 (1 F)	10.1 (1.5) 10.0 (1.6)	97.5 (19.2)[a] 114.6 (8.2)[a]	DNR	8.86 (5.3)[b] 14.6 (1.3)[b]	AUT below chance identifying words from nonwords; NT above chance. NT: increases in activation to nonwords compared to words in primary auditory cortex, pSTG, and IFG; no surprisal effect in AUT.

Note: The table is organized first by methodology (behavioral, imaging), then by modality (visual, auditory, multimodal), and then by alphabetical order of first author. Group differences compared Autism (AUT) to Neurotypical (NT) groups unless otherwise noted. Behav = behavior; Electroencephalography (EEG); Magnetoencephalography (MEG); Serial reaction time (SRT); Did not report (DNR); Full-Scale IQ (FSIQ); nonverbal IQ (NVIQ); IQ-matched NT control group (IQ-M); Age-matched NT control group (Age-M); Two-alternative forced choice (2AFC); Reaction time (RT); Statistical learning (SL); Restricted and repetitive behaviors and interests (RRBI); Social responsiveness scale (SRS); Average (avg); Posterior superior temporal gyrus (pSTG); Inferior frontal gyrus (IFG). Note that none of these studies utilized Bayesian statistical approaches

[a]values represented as standard scores

[b]values represented as scaled scores

[c]Comparison group other than a NT group (e.g., specific language impairment (SLI))

* IQ not reported at the group level and/or were measured utilizing multiple methods, therefore the text description was used

** Verbal abilities were measured using the verbal milestone subdomain on the VB-MAPP, which assesses language milestones achieved at age 48 months and is scored out of 170 points

anced, practice effects may have impacted task performance or participants' understanding of task characteristics (e.g., a more explicit understanding of task demands, namely finding pairs or patterns within the sequences).

Neuroimaging results

Word and tone segmentation Four studies utilized imaging techniques: EEG [56, 61], fMRI [63], and MEG [64]. Arnett et al., 2018 and Wagley et al., 2020 matched on age and sex, while Scott-Van Zeeland et al., 2010 matched on age and full-scale IQ, and Li et al., 2020 did not perform any matching. Unlike the behavioral paradigms, learning was assessed by neural response differences during passive listening rather than on explicit recognition or recall tests. Using EEG, Arnett et al. (2018) found no group differences for P1 amplitude or latency, suggesting similar links between basic auditory processing and language processing in both groups. In the autism group, individuals with stronger receptive language had more attenuated P1 amplitude for learned versus novel words (suggesting that words required less effort and processing), representing a link between language ability and statistical learning. Li et al. (2020) found a similar relationship between verbal ability and neural measures of statistical learning; their results showed higher gamma power in NT versus both verbal and minimally verbal autistic groups. Across groups, verbal abilities and gamma power were positively associated in temporal regions and negatively associated in right frontal regions. Taken together, these EEG findings highlight the relevance of language abilities, over and above diagnostic group membership.

Using functional MRI (fMRI), Scott-Van Zeeland et al. (2010) found that, for NT but not autistic individuals, activity in fronto-temporal-parietal networks decreased as the number of cues to word boundaries increased, reflecting less effortful processing of the speech stream. In addition, they found gradual signal increases with increasing word boundary cues in basal ganglia and left temporo-parietal cortex for NT but not autistic participants. The severity of language impairment was inversely associated with signal increases in basal ganglia and left temporo-parietal cortex in the autism group, highlighting the importance of language abilities over and above diagnostic group, as in the EEG studies. Using MEG, Wagley et al. (2020) found increased activation to nonwords versus words (a "surprisal" effect) in primary auditory cortex, posterior superior temporal gyrus, and inferior frontal gyrus for NT but not autistic individuals, suggesting minimal learning in the autism group.

Across behavioral and imaging auditory statistical learning studies, behavioral statistical learning abilities across autistic groups were generally indistinguishable

Table 3 Summary of findings from the autistic group across modalities and methodologies

Modality	Methodology	Evidence of learning differences between NT and AUT
Auditory	Behavioral	No
	Neuroimaging	Mixed
Visual	Behavioral	No
	Neuroimaging	Mixed
Audiovisual Integration	Behavioral	No, but small number of studies

from their NT peers; however, alternative neural mechanisms gave rise to the same behavioral outcomes; Fig. 2. Results suggest that compensatory mechanisms in the autistic brain facilitate learning, with more brain regions involved and more effortful processing. However, beyond diagnostic status, cognitive and language abilities impact the ease and success with which individuals across groups learn from auditory statistical regularities.

Visual statistical learning

Behavioral results

Object and letter sequence segmentation Two behavioral studies [59, 65] examined object sequence segmentation abilities and one study [59] additionally examined letter sequence segmentation abilities in children and adults. Hu et al., 2023 matched groups on age, whereas Parsons and Baron-Cohen, 2023 did not perform matching. Both Hu et al. (2023) and Parsons and Baron-Cohen (2023) found no group differences in object sequence segmentation accuracy, with both groups performing above chance. However, Parsons and Baron-Cohen (2023) found lower accuracy in the autism group for learning of visual exemplars when testing included exemplars that were not included in the training set (i.e., generalization). For letter sequence segmentation, Hu et al. (2023) found lower accuracy in the autism group, with verbal abilities positively associated with accuracy (similar to their auditory word segmentation results). Again, it is important to note that the analytic approach (z-score composites) employed in Hu et al. (2023) differs significantly from those employed in each of the three other studies, reducing the comparability with other studies.

Contextual cueing Eight behavioral studies [66–73] examined contextual cueing in children, adolescents, and adults. All studies matched participants on age, while Barns et al., 2008 additionally matched on full-scale IQ and sex, Jiang et al., 2013 on nonverbal IQ and sex, Kourkoulou et al., 2013 on full-scale, nonverbal, and verbal IQ, Schuwerk et al., 2016 on verbal and nonverbal IQ, and Travers et al., 2013 on nonverbal IQ. Six of these studies [66–68, 70, 71, 73] reported no group differences in overall learning or learning rate (as measured by decreased RT over learning trials), though the autism group had generally slower RT. Kourkoulou et al. (2013) found slower first saccades and longer fixation duration during visual search in the autism group, contributing to the slower RTs. Barnes et al. (2008), Brown et al. (2010), and Jiang et

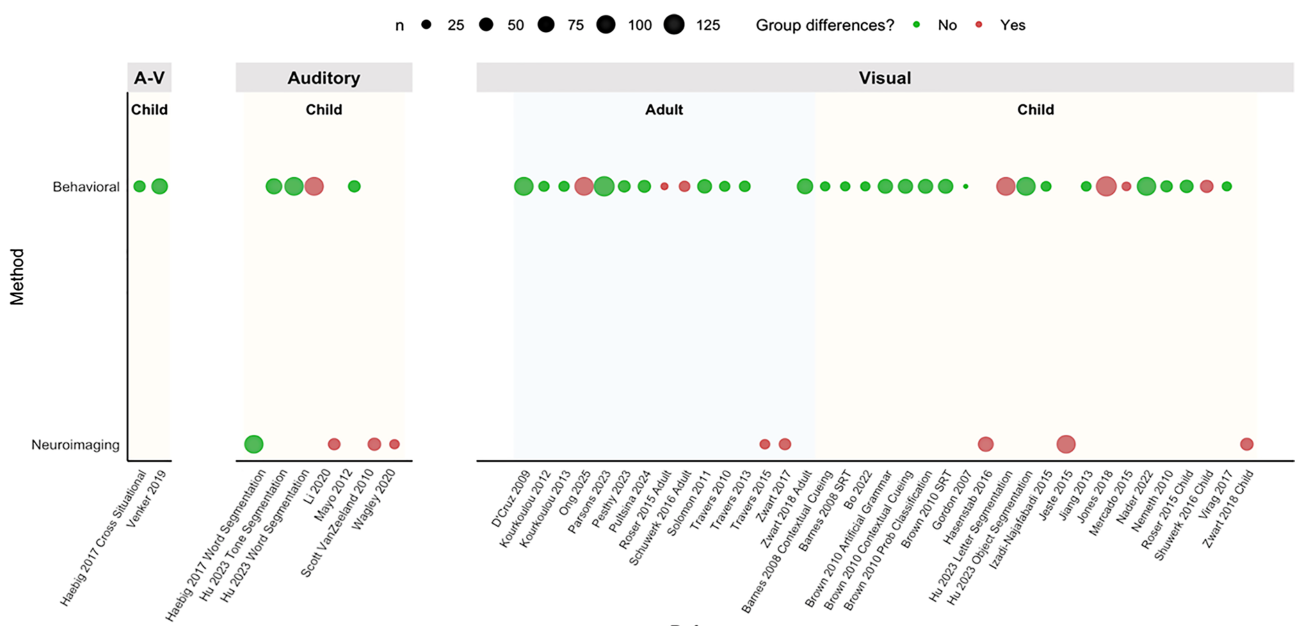

Fig. 2 Summary of findings. Studies are sorted along three dimensions: modality (audio-visual, auditory, or visual), method (behavioral or neuroimaging), and age (child/adolescent or adult). Dot size for each study reflects sample size; larger dots indicate larger samples. Color indicates ASD versus NT sample differences; green represents no group differences and red indicates statistically significant group differences

al. (2013) found a greater RT decrease in the autism compared to the NT group, showing *greater* learning. However, Travers et al. (2013) found that the autism group learned less effectively from cues that were present at the global but not local level, suggesting an important role of cue proximity to the target.

Two studies [69, 72] found less consistent results. Schuwerk et al. (2016) found no learning in the autism group after repeated exposure to predictive visual scenes; note that their task design differed from those in other studies such that the information was presented via movies with a story line as opposed to more simplified visual scenes. Jones et al. (2018) found different patterns of RT changes (learning): In the autism group, RT decreased linearly for both high and low frequency visual scenes, suggesting steady, but slow learning rates, whereas the NT group had relatively flat RT slope (indicating quick learning) for high frequency scenes and inverse quadratic slope (i.e., benefit from additional practice later in the task) for low frequency scenes. Autistic individuals with low social responsiveness scale (SRS) scores (i.e., less autistic characteristics in the social domain) had similar RT trajectories to the NT group for high frequency scenes. Autistic participants with high verbal abilities generally had a more NT-like RT trajectory for both conditions. Across contextual cueing studies, results suggest that autistic groups were generally indistinguishable from their NT peers, though findings are somewhat mixed as to the efficiency with which learning occurred. In addition, individual differences in social responsiveness and language abilities appear related to learning performance, such that those with less autistic characteristics and better language abilities learn more efficiently.

Serial reaction time (SRT) A total of 11 studies examined serial RT behavioral performance in children, adolescents, and adults [51, 55, 57, 60, 66, 67, 74–78]. All studies but Zwart, Vissers, and Maes matched groups on age. In addition, Barnes et al., 2008 matched on full-scale IQ and sex, Bo et al., 2022 and Brown et al., 2010 on sex, Izadi-Najafabadi et al., 2015 on handedness, Travers et al., 2010 on verbal IQ, and Nemeth et al., 2010, Virág et al., 2017, and D'Cruz et al., 2009 on full-scale IQ. All eleven behavioral studies found evidence of learning (decrease in RT over the course of exposure). Most studies found no group differences in the magnitude of learning, though one study [60] found a greater magnitude of learning in the NT group, and another found a greater magnitude of learning in the autism group [66]. As with contextual cueing results, Brown et al. (2010), Gordon and Stark (2007), and Travers et al. (2010) found slower RT in the autism group, though Barnes et al. (2008) and Pesthy et al. (2023) found no group RT differences. In addition, some studies found that the autism group benefitted from extended practice [67] or from a break for learning consolidation which resulted in decreased RT [75]. Bo et al. (2022) found a positive correlation between the magnitude of learning and motor abilities for individuals with faster RTs across groups; this trend did not hold for those with slower RT. Similarly, Zwart, Vissers, and Maes (2018) found a positive association between SRS scores and RT for the autism group for deterministic, but not probabilistic, sequence learning, suggesting a benefit for more strongly predictive sequences. Gordon and Stark (2007) found no evidence of learning at the individual level within the autism group with complex sequences (e.g., eight items long), though some autistic individuals were able to learn simpler sequences (e.g., four items long). Across these studies, results suggest autistic groups were generally indistinguishable from their NT peers, though autistic group reaction time appeared to be slower than their NT peers. Similarly to contextual cueing, social responsiveness appears related to learning performance, such that those with less autistic characteristics learn more efficiently.

Probabilistic classification Six behavioral studies [50, 52, 54, 67, 79, 80] examined probabilistic classification performance in adolescents and adults. All studies except for Solomon et al., 2011 matched groups based on age. Additionally, Brown et al. (2010) matched on sex, Mercado et al. (2015) and Pultsina et al. (2024) on sex and full-scale IQ, and Nader et al., 2022 on perceptual reasoning composite from the WISC-IV and the spatial span subtest score also from the WISC-IV. Groups did not differ in performance in four studies Brown et al. (2010), Nader et al. (2022), Pultsina et al. (2024), and Solomon et al. (2011), though Nader et al. (2022) reported enhanced performance in autism when classification information was presented simultaneously and Solomon et al. (2011) reported enhanced performance in autism for low probability pairs during the early learning phase. However, Ong et al. (2025) found contrary evidence, such that the autism group showed lower performance compared to the NT group when the associations were weakly predictive. Mercado et al. (2015) however, reported two distinct patterns in the autism group across learning trials. When items were presented with a consistent number of objects across trials, some autistic individuals showed learning (i.e., accurate differentiation of category and non-category members), with no difference from the NT group, where others performed at chance. However, when the number of objects presented during the learning trials varied, some autistic individuals continued to show learning, whereas others who had learned during the consistent trials now showed chance-level performance. No demographic variables accounted for this variability in performance.

Within the context of generally above chance performance on probabilistic classification tasks, Pultsina et al. (2024) looked at how general arousal (as measured by pupillary dilation) may differ between autistic and NT individuals during the learning process. Interestingly, they found that, while the groups behaviorally performance similarly, learning caused increased pupillary arousal for the autism group, with the opposite holding true for the NT group. Additionally, greater pupillary arousal was positively correlated with a greater degree of self-reported intolerance for uncertainty in daily life.

Artificial grammar learning A behavioral study [67] examined artificial grammar learning in adolescents, with groups matched on age, sex, and full-scale IQ, and found no group differences in discriminating grammatical from ungrammatical sequences.

Visual scene A behavioral study [81] examined statistical learning of probabilistically determined visual scenes in children and adults and found that autistic adults outperformed NT adults on 2AFC tasks; the child groups did not differ. For children, groups were matched on age alone, whereas adults were matched on age, full-scale IQ, and handedness. The authors suggested that enhanced performance in autistic adults may reflect an attentional bias to local details of complex visual arrays.

Across behavioral visual statistical learning studies, overall performance in the autism group appeared relatively indistinguishable from NT peers, though they were generally slower; Fig. 2. In addition, autistic individuals appeared to benefit from increased exposure, time to consolidate learning, and more explicitly presented patterns than their NT peers. As with auditory statistical learning, cognitive abilities (i.e., language), motor abilities, and severity of autism symptomatology (i.e., social difficulties) impact one's ability to track and extract the statistical regularities of the visual environment above and beyond diagnostic status. However, it is important to note that studies varied widely on their group matching procedures, which may impact the interpretation of findings.

Neuroimaging results

Object and letter sequence segmentation Two studies utilized EEG [53, 58] to measure online learning. Both studies matched participants based on age. In general, these studies compare neural responses to "trained" versus untrained stimuli, after a period of exposure (that is presumed to stimulate learning); when the amplitude (strength) or latency (timing) of the evoked responses differs as a function of condition, this indicates that the participant has learned something meaningful about the stimuli. In a study aimed at ERP methods development, Hasenstab et al. (2016) reported a positive mean differentiation of P3 amplitude for learned vs. novel stimuli in autism but a negative differentiation in the NT group; differentiation of this component suggests increased attention to one category of stimuli. Some individual autistic participants showed flat differentiation (e.g., no distinction between learned and novel stimuli), and some NT participants showed positive differentiation (e.g., a similar pattern to those in the autism group). No autistic participants showed the negative differentiation displayed by the NT group. Similarly, Jeste et al. (2015) found significant N1 responsivity to learned versus novel events in NT but not autistic participants, suggesting learning in the NT group alone. In addition, there was a positive association between N1 amplitude and nonverbal abilities, and between P300 amplitude and social abilities, in the autism group, further suggesting that the ERP effects were indexing a clinically meaningful response. Somewhat puzzlingly, autistic individuals with high nonverbal abilities displayed a positive N1 response; autistic individuals with low nonverbal abilities, and NT individuals, showed a negative N1 response. Similarly, autistic individuals with high social abilities displayed a positive P300 response, whereas autistic individuals with low social abilities and NT individuals showed a negative P300 response. Findings from this study indicate a strong relationship between nonverbal and social abilities and visual statistical learning abilities; group differences in the directionality of relationships suggest that autistic individuals with stronger abilities may rely on different (potentially compensatory) neural mechanisms to learn, relative to NT individuals (who did learn) and those with weaker abilities (who did not learn).

Serial reaction time (SRT) A total of three studies examined serial RT performance utilizing neuroimaging in children, adolescents, and adults [82–84]. All studies matched participants on age, while Travers et al., 2015 and Zwart et al., 2017 additionally matched on full-scale IQ and Zwart, Vissers, Kessels et al., 2018 on nonverbal IQ and sex. An fMRI study [82] found decreased activation during SRT in right parietal lobule and right precuneus during learning in the autism group. Differences in activation were associated with RT differences between high and low probability sequences; that is, greater activation was associated with steeper slope of RT change, indicating learning similar to the NT group. In addition, RT differences were associated with restricted and repetitive behaviors and interests (RRBI) severity, such that those with greater symptom severity showed less RT differentiation across probability levels.

Two EEG studies [83, 84] found contradictory results. Zwart et al. (2017) reported frontal P3, but not frontocentral N2b, enhancement for novel sequences in the autism group, with the opposite relationship in the NT group. Behaviorally, there were no group differences in RT. This result suggests that different neural mechanisms underlay learning across groups. However, Zwart, Vissers, Kessels, et al. (2018) found central N2b, but not frontal P3, enhancement throughout learning in the autism group, but only during early stages of learning in the NT group. As with Zwart et al. (2017), there were no group differences in RT; however, the relationship between N2b and P3 activation and learning in autistic individuals remains unclear.

Across imaging visual statistical learning studies, it remains relatively unclear what neural mechanisms underly generally successful behavioral performance within the autistic group; Fig. 2. As with auditory statistical learning, it appears that autistic individuals are utilizing compensatory mechanisms to support learning, though the specific mechanisms are not well established, especially when measured utilizing EEG. However, a central theme is that cognitive abilities (including language) and severity of autism symptomatology (i.e., RRBI's) impact the way in which the brain tracks and extracts the statistical regularities of the visual environment, above and beyond clinical diagnostic status alone.

Multimodal statistical learning

Cross-situational word learning Two studies [45, 85] examined cross-situational word learning in children and adolescents, utilizing eye movements to index learning. Haebig et al., 2017 matched participants on age and full-scale IQ, while Venker et al., 2019 did not perform matching procedures. Both studies reported no group differences on performance (e.g., both NT and autism groups looked longer to the target than the distractor images); Fig. 2. In addition, both studies found that participants with stronger language abilities looked more to the target image during test trials, suggesting that language acquisition was linked to experimental word learning. While few studies have tackled multi-modal statistical learning, results consistently suggest no group differences in learning abilities in this domain.

Discussion

Statistical learning, or the ability to detect, track, and extract the predictive relationships between events in the sensory environment, has been hypothesized as an underlying cognitive deficit that gives rise to social, RRBI, and language difficulties in autism. Given the numerous studies examining these processes, and the conflicting findings to date, this systematic review sought to clarify the impact of sensory modality, methodology, and task design on the findings of statistical learning abilities in autistic individuals.

The impact of modality on statistical learning

Across modalities, the auditory and visual literatures presented mixed findings. The multimodal literature was more consistent, though it includes only two studies to date; as such, the multimodal results must be interpreted with caution. In the auditory modality, only seven studies assessed word and tone sequence segmentation, with some studies finding no differences between autism and NT groups [45, 56, 59, 62] and others finding relatively worse performance in the autism group (Hu et al., 2023) or differential neural activcation (Li et al., 2020; Scott-Van Zeeland et al., 2010; Wagley et al., 2020). As predicted, the neuroimaging studies showed the greatest variability in results, with one EEG study [56] showing similar neural mechanisms between autistic and NT individuals, and the other [61] showing evidence of differential neural activation. In addition, the fMRI [63] and MEG [64] studies showed evidence of differential neural mechanisms. Across all imaging studies, the neural mechanisms and brain areas underlying performance varied between studies, leaving an open question as to what might be leading to differences observed at the behavioral level.

Similarly, within the visual domain, the majority of studies reported no group differences in statistical learning abilities; all utilized behavioral measures. However, there was wide variability in the underlying neural mechanisms and brain areas implicated across both groups. Again, this leaves an open question as to the brain-behavior link within statistical learning abilities in autism. One possible interpretation is that similar behavioral outcomes may arise from different neural routes, supporting a compensatory neural mechanisms hypothesis in which autistic individuals recruit alternative brain regions to achieve comparable learning performance.

The multimodal results painted the clearest picture of statistical learning abilities across modalities, however, this literature only included two cross-situational word learning studies at the time of this review [45, 85]. Both behavioral studies reported no group differences in statistical learning abilities when integrating auditory and visual information, with above-average task performance and no group differences. Taken together, these findings suggest that modality is likely not the primary contributor to the wide variability observed across studies, given the significant number of results showing no group differences in statistical learning abilities. We turn to methodological factors and individual differences within autistic samples, as these contribute more to variable findings. An alternative domain-interaction hypothesis could explain these results, suggesting that the influence of statistical learning in autism depends not on modality alone but on the interaction between sensory domain and cognitive or linguistic demands.

The impact of methodology

Task design

Across modalities, seven unique tasks were utilized, all of which vary in task demands (e.g., passive versus active responding), stimulus format (e.g., continuous streams that provide one bit of information at a time versus complex visual arrays), and outcome measure (e.g., RT, choice behavior, eye gaze, etc.). This variability is multiplied by 'researcher degrees of freedom' in instructions, stimulus characteristics, number of trials, and experimental setup. The most-utilized paradigm was the SRT task (used in 14 out of 37 studies). Across all 14 SRT studies, there were no group differences in statistical learning as shown by changes in RT, though effect sizes varied across studies.

The next-most utilized paradigms were sequence segmentation (10 studies) and contextual cueing (eight studies). For the sequence segmentation paradigm, four studies found *definitive* evidence of learning [45, 56, 62, 65], three found *some* evidence of learning [58, 59, 61], and three found *no* evidence of statistical learning in autism, as compared to NT performance or neural activation [53, 63, 64]. Similarly, for the contextual cueing paradigm, five studies found *definitive* evidence of learning [66–68, 70, 71], two found *some* evidence of learning [69, 73], and one found *no* evidence of statistical learning in autism [72]. The remaining paradigms, including probabilistic classification (six studies; [50, 52, 54, 67, 79, 80], cross-situational word learning (two studies; 37,73), artificial grammar learning (one study; 55), and visual scene (one study; 69), all suggested *typical learning* in autistic individuals. Despite the small number of studies in each category, the relatively consistent results across task designs would suggest that these seven paradigms tap into similar statistical learning cognitive processes. However, a task-demand sensitivity hypothesis could explain residual variability across paradigms, proposing that differences in task structure, explicitness, and attentional requirements uniquely impact performance among autistic participants.

Outcome measure: behavioral vs. neuroimaging

Across modalities and paradigms, 28 studies were primarily behavioral and nine studies were primarily neuroimaging. Across behavioral studies, 23 showed *definitive* evidence of learning [45, 51, 52, 54, 55, 57, 60, 62, 65–71, 74–76, 78–81, 84, 85], four showed *some* learning [50, 59, 69, 73], and one showed *no* learning [72]. The behavioral evidence suggests generally typical statistical learning abilities in autism.

In contrast, results of the nine imaging studies were less consistent. Two reported no group differences in neural processing [56, 84], two reported divergent results in the autism group, with the lower language abilities group exhibiting similar processes to NT individuals and the neural mechanisms of the higher language abilities group's diverging from NT peers [58, 61]. Five studies reported divergent neural processes underlying online statistical learning [53, 63, 64, 77, 78, 83]. While these differences do not indicate an *impairment* in statistical learning, findings do suggest striking variability in the neural mechanisms that underlie statistical learning in autism. For some autistic individuals, neural function during online learning resembles NT peers; for others (and generally those with stronger language abilities), neural mechanisms of statistical learning capture different brain regions, more active learning strategies, or different attentional mechanisms. These changes could be described as compensatory, though more specific hypotheses regarding *where* and *how* this neural compensation occurs are far from clear. Future research could directly test this compensatory mechanism hypothesis by examining whether differential neural activation patterns predict comparable behavioral performance, thereby clarifying the relationship between neural efficiency and learning outcomes.

The variability across studies reflects differential findings for behavioral versus neuroimaging approaches, rather than task design. Of course, future studies should systematically explore the convergent validity of each task design as a means of assessing statistical learning abilities. Finally, two factors not addressed in this review are the important roles of instruction type (e.g., explicit vs. implicit) and feedback to the learner (during exposure or during a supervised condition); we refer readers to a recent review that critically analyzes methodological approaches to statistical learning research [42].

Individual differences in statistical learning in autism

The most consistent finding across studies was that individual differences, including verbal and nonverbal abilities, autistic characteristics (including social functioning and RRBIs), and motor abilities, play an integral role in the heterogeneity of statistical learning in autism. Researchers should collect, report, and integrate these variables to allow for nuanced interpretation of both behavioral and neuroimaging results. This review also highlights the need to include participants with a wide range of abilities, given their significant influence on statistical learning. An individual-differences hypothesis may therefore provide a unifying account for the mixed findings, suggesting that variability in statistical learning reflects heterogeneity in cognitive, linguistic, and social profiles rather than a universal group-level difference.

Individual differences in statistical learning in autism

Many studies found associations between statistical learning and verbal and nonverbal abilities. Within the domain of language, four studies found an association between language abilities and behavioral measures (cross-situational word learning, word and letter sequence segmentation, and nonverbal contextual cueing) of statistical learning. Additionally, three studies found links between language abilities and underlying neural mechanisms of statistical learning, with the latter including attenuated P1 amplitude (that is, a less effortful response), gamma power in right frontal and temporal regions, and lesser signal increases in basal ganglia and left temporo-parietal cortex. Together, these results suggest that stronger language abilities may require less effort or attention during learning, and that verbal abilities appear to facilitate statistical learning. This is consistent with findings that verbal abilities are associated with performance of even putatively non-verbal cognitive tasks [86]. This pattern is consistent with the individual-differences hypothesis, implying that language-related variability contributes to how efficiently individuals detect and generalize statistical regularities.

Within the nonverbal domain, Jeste et al., (2015) found an association between nonverbal abilities and N1 amplitude, in that those with high nonverbal abilities had significantly different N1 activity compared to both those with low nonverbal abilities and NT individuals. This result indicates a strong relationship between nonverbal abilities and visual statistical learning abilities, though the directionality of the relationship suggested that autistic individuals with high nonverbal abilities utilize differential neural mechanisms to learn; those with lower abilities, who also demonstrated reduced learning, do not. This may further support the idea that multiple learning routes exist within autism, potentially reflecting both compensatory and ability-dependent mechanisms.

Core features of autism (social functioning and RRBIs)

Several studies examined associations between statistical learning and autism characteristics. Findings revealed that social abilities (SRS scores) were associated with more typical learning trajectories [69] but were associated with *more* atypical P300 responses [58]. Greater activations during learning in regions associated with imagery and visual memory were correlated with reduced RRBIs [82]. These results suggest a strong relationship between core autism features (social communication, RRBIs) and statistical learning at both the behavioral and neural level, and could also suggest that the RRBIs hinder the ability to attend to and learn probabilities within event sequences. Some studies also reported associations between statistical learning performance and stronger motor abilities [60, 71], but these results suggest that motor skills are more critical for *task performance* than for learning abilities. Given that many learning tasks rely on RT as an outcome measure, motor abilities present a confound. Collectively, these patterns lend support to the notion that variability in statistical learning reflects individual and neural adaptations rather than a single underlying deficit, aligning with the compensatory mechanisms and individual-differences hypotheses described above.

Clinical implications

Understanding statistical learning and its underlying neural mechanisms is critical to an evidence-based approach to intervention. Clinical trials show interventions lead to significant gains in cognitive abilities, spoken language, and reductions in disruptive behaviors [87]. Developmentally and socially relevant behavioral interventions, such as the Early Intensive Behavioral Intervention (EIBI; [88]), Early Start Denver Model (ESDM; [89]), Joint Attention, Symbolic Play, Engagement and Regulation (JASPER; [90]), and Early Achievements [91], are based on core principles of learning and behavior; treatment goals are formulated and addressed via basic learning principles such as positive reinforcement and understanding of the antecedents and consequences of behaviors [92]. Positive reinforcement *requires* tracking probabilistically determined events; for example, each time a child uses a targeted behavior, they receive positive feedback that promotes further use of that behavior. Successful feedback requires the individual to track the association between behavior and feedback. Similarly, speech and language interventions require the tracking of cooccurrences across modalities (as in cross-situational word learning and artificial grammar learning), and such tracking is tightly correlated with broader language abilities [45, 85]. Speech/language interventions involve matching pictures to ideas (e.g., in picture exchange communication system; PECS). Therefore, statistical learning abilities are likely related to intervention efficacy, though the empirical literature on statistical learning in autism does not clearly indicate whether and how statistical learning abilities differ from non-autistic peers. The most consistent finding across studies was the important role of individual differences across other cognitive and clinically meaningful domains (e.g., cognitive abilities, language abilities, autism-specific traits) in both behaviorally measured statistical learning abilities and the neural mechanisms that underly them. Therefore, a richer understanding of the role of individual differences in statistical learning abilities will be crucial for improving the delivery of individualized interventions. Future studies should focus on leveraging new emerging empirical methodology, such as neuroimaging and computational modeling, that allow for within-subject, as opposed to group level, analyses, to further characterize specific clinical profiles.

Limitations

Studies to date have focused on individuals within a limited cognitive range (87% of studies had a full-scale and nonverbal cognition scores in the average range), largely excluding autistic individuals with below-average cognitive abilities [93]. Studies have been somewhat more inclusive of individuals with language difficulties, with 33% of studies including individuals with lower-than-expected standardized language scores. Zero studies to date have included individuals with minimal or non-speaking verbal abilities, who make up an estimated 30% of the autistic population [22–25]. In addition, many studies selectively matched participants based on cognitive abilities (e.g., full-scale, verbal, or nonverbal IQ), in addition to age and sex, further homogenizing a heterogeneous sample.

These participant demographics reflect the demands of participation; in most experimental paradigms, especially eye tracking and neuroimaging tasks, participants must comprehend instructions and remain still for extended periods. To broaden the participant base, researchers should consider the use of passive tasks (e.g., sequence segmentation), which do not require a specific behavioral response and thus can be adapted for individuals with weaker cognitive abilities. Even passive tasks may require training, protocol modification (e.g., shorter runs, frequent breaks, etc.) or modified analytic approaches to accommodate movement artifacts. Some methods, such as EEG or fNIRS, are more robust to participant variability in movement, but also pose sensory challenges (e.g., tolerating an electrode cap). Creative approaches to including a wide range of participants are needed to deepen our understanding of individual differences in statistical learning abilities, while minimizing harm and discomfort [94, 95].

Another limitation reflects the lack of sociodemographic variability. All studies in this review were male-biased; reflecting the estimated 4:1 male: female ratio in autism [96]; five included *only* males. While studies of neurotypical populations report no sex differences in *behavior*, there are consistent sex differences in *brain structure and function* of brain regions critical to statistical learning (e.g., increased relative hippocampal volume in females; [97, 98]). Future research should systematically evaluate sex differences. Similarly, most studies did not report race, ethnicity or socioeconomic status, reducing the interpretability and replicability of findings [99–101]. Methods such as EEG and fNIRS are impacted by hair structure and skin pigmentation [102, 103]; research that includes primarily White and high-socioeconomic-status participants leads to inaccurate prevalence estimates and to ongoing disparities in access to diagnosis and intervention services [96, 104, 105].

A final limitation of the present review is that most of the included studies did not report effect sizes, which limits our ability to compare findings quantitatively across studies and to draw conclusions about the magnitude of observed effects. This gap highlights the need for greater methodological transparency and consistency in future research. Future studies should systematically calculate and report effect sizes alongside traditional statistical significance testing, as this would enhance comparability, facilitate meta-analytic synthesis, and strengthen the evidence base.

Conclusions and future directions

The aim of this review was to examine the impact of sensory modality, methodology, and task design on statistical learning abilities and their impact on cognitive and language abilities in autistic individuals. Behaviorally, results indicated minimal group differences in statistical learning abilities across sensory modality and task design, with the caveat that significantly more studies focused on the visual as compared to auditory and multimodality domain; additional work is needed in the latter areas. Interestingly, few studies have evaluated convergent validity across tasks [44]; a comparison or a meta-analytical analysis across the seven commonly used task designs would be of high interest.

Imaging results were exceptionally inconsistent, with many studies reporting differential neural activity in autistic individuals relative to neurotypical groups and comparing verbal with less-verbal autistic subgroups. There was limited converging evidence implicating specific brain regions or neural mechanisms; the role of neural processes in autistic statistical learning is poorly understood. Future studies must include participants with a wide range of abilities.

The greatest influences in study results were methodological, along with individual differences in verbal, nonverbal, social, and motor abilities, and severity of RRBIs. The individual variables that impact statistical learning abilities may be associated with broader statistical learning abilities in autism [106], providing some support for the Prediction in Autism (PIA) hypothesis. However, it remains unclear which is the driving force – that is, do autistic characteristics somehow contribute to reduced statistical learning abilities, or do limitations in statistical learning lead to the features of autism? Deficits in statistical learning are conceptualized as the driving force behind atypical social and language functioning and RRBIs; however, cross-sectional studies cannot capture causative relationships. Thus, intervention and longitudinal studies that promote statistical learning skills are needed as a true test of the PIA Hypothesis. In addition, studies largely focus on the relationship between the input stimulus and the outcome variables, leaving the underlying mechanisms that support statistical learning unknown. The underlying mechanisms themselves are likely the most important factors to consider when assessing individual differences in learning trajectories. It is likely that none of the current methods of studying statistical learning have the current ability to assess these mechanisms, so further exploration and clarification will require innovative new study designs to further our knowledge of statistical learning.

Clinical intuitions have long suggested that statistical learning deficits might explain some of the challenges and characteristics of autism. While the behavioral data are generally inconsistent with this hypothesis, imaging data reveal significant differences in how learning is processed by the brain. Further, we have only tested higher-ability participants and those from majority sociodemographic groups. Together, these findings would suggest that there is more work to be done to assess the role of statistical learning in autism.

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Author contributions
RRB conceived of the study, and led writing of the introduction, methods, and discussion, with critical revisions by IME, HRT, and JRS. HRT assisted with abstract review reliability. Funding acquisition was led by IME and RRB.

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