

Exploiting ChatGPT for Diagnosing Autism-Associated Language Disorders and Identifying Distinct Features

Xin Li

xli48@albany.edu

xli48@albany.edu https://orcid.org/0000-0003-2067-2763

Chuanbo Hu

University at Albany

Wenqi Li

West Virginia University

Mindi Ruan

West Virginia University

Xiangxu Yu

Washington University in St. Louis

Lvnn Paul

California Institute of Technology

Shuo Wana

Washington University in St. Louis

Article

Keywords: Autism spectrum disorder, Language deficits, Machine learning, Large language models, ChatGPT

Posted Date: May 21st, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4359726/v1

License: © ① This work is licensed under a Creative Commons Attribution 4.0 International License.

Read Full License

Additional Declarations: (Not answered)

Exploiting ChatGPT for Diagnosing Autism-Associated Language Disorders and Identifying Distinct Features

Chuanbo Hu¹, Wenqi Li^{1,4}, Mindi Ruan⁴, Xiangxu Yu³, Lynn K. Paul², Shuo Wang³, Xin Li¹

^{1*}Department of Computer Science, University at Albany, Albany, 12222, NY, USA.
²Humanities and Social Sciences, California Institute of Technology, Pasadena, 91125, CA, USA.

³Department of Radiology, Washington University in St. Louis, St. Louis, 63110, MO, USA.
⁴Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, 26506, WV, USA.

Contributing authors: chu3@albany.edu; wl00021@mix.wvu.edu; mr0114@mix.wvu.edu; xiangxu@wustl.edu; lkpaul@hss.caltech.edu; lkpaul@hss.caltech.edu; xli48@albany.edu;

Abstract

Diagnosing language disorders associated with autism is a complex and nuanced challenge, often hindered by the subjective nature and variability of traditional assessment methods. Traditional diagnostic methods not only require intensive human effort but also often result in delayed interventions due to their lack of speed and specificity. In this study, we explored the application of ChatGPT, a state-of-the-art large language model, to overcome these obstacles by enhancing diagnostic accuracy and profiling specific linguistic features indicative of autism. Leveraging ChatGPT's advanced natural language processing capabilities, this research aims to streamline and refine the diagnostic process. Specifically, we compared ChatGPT's performance with that of conventional supervised learning models, including BERT, a model acclaimed for its effectiveness in various natural language processing tasks. We showed that ChatGPT substantially outperformed these models, achieving over 13% improvement in both accuracy and F1-score in a zero-shot learning configuration. This marked enhancement highlights the model's potential as a superior tool for neurological diagnostics. Additionally, we identified ten distinct features of autism-associated language disorders that vary significantly across different experimental scenarios. These features, which included echolalia, pronoun reversal, and atypical language usage, were crucial for accurately diagnosing ASD and customizing treatment plans. Together, our findings advocate for adopting sophisticated AI tools like ChatGPT in clinical settings to assess and diagnose developmental disorders. Our approach not only promises greater diagnostic precision but also aligns with the goals of personalized medicine, potentially transforming the evaluation landscape for autism and similar neurological conditions.

Keywords: Autism spectrum disorder, Language deficits, Machine learning, Large language models, ChatGPT

1 Introduction

Autism spectrum disorder (ASD) is a developmental condition characterized by challenges in social interaction, restricted interests, and repetitive behaviors [1–3]. The spectrum of ASD symptoms is broad, with communication difficulties often standing out as the most significant and impacting aspects of the disorder [4–6]. These symptoms manifest differently across various age groups. In adults, communication difficulties are particularly pronounced and can significantly impact social integration and personal development [7, 8]. Properly identifying and understanding these communication issues in adults is crucial for effective intervention and support.

Language disorders in adults with ASD include a wide range of issues, from the absence of speech to subtle impairments such as echolalia (repetitive use of phrases or sounds), pronoun reversal, and pragmatic language impairments [9–11]. These disorders can hinder effective communication and pose significant challenges in

social and occupational settings. Accurate and early identification of these language anomalies is essential for providing appropriate therapeutic interventions that can significantly enhance the quality of life for adults with ASD.

While the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2) [12] is a gold standard for ASD diagnosis across various age groups, its application, especially in adults, can be limited by the subjective interpretations required of human clinicians. Traditional methods are not only time-consuming but also prone to inconsistencies due to varied human judgment, which can affect the reliability of diagnosing complex language and social communication issues in adults.

Large language models (LLMs) have the potential to transform the practice of precision medicine [13] and personalized healthcare [14]. For example, LLMs can analyze vast amounts of medical literature and patient data to provide personalized medical advice. Considering an individual's medical history, genetic information, and lifestyle, these models can suggest tailored health recommendations, treatments, and preventive measures. Meanwhile, LLMs can serve as advanced decision-support tools for healthcare providers by offering up-to-date medical information, diagnostic suggestions, and treatment options based on the latest research findings. This support is crucial in handling complex cases such as autism spectrum disorder (ASD) where multiple disorders or conditions may affect the patient.

Connecting LLMs with ASD is still an emerging field that has not attracted much attention as of today for the following reasons. First, popular LLMs such as BERT [15] and ChatGPT [16] are trained on general text repositories without any domain knowledge injected. It requires fine-tuning LLMs on ASD-related datasets to leverage their power for supporting the diagnosis and intervention of ASD. Second, ASD is characterized by sophisticated social communication and interaction behaviors, including language skills. However, language skills alone are insufficient for a reliable diagnosis of ASD. How to combine language disorders in ASD with other salient biomarkers (e.g., gaze and stimming related [17]) remains an under-researched topic. Third, unlike other neurological disorders such as depression and anxiety, ASD is a developmental disorder, which make its data collection challenging. In addition to privacy concerns, ASD can be confused with the delay in language development among young children [18]. In other words, the potential use of LLMs under the ASD context has to properly take inevitable bias into account [19].

In this study, we employed machine learning and LLMs to investigate language deficits in ASD by the following motivations:

- Advancement in Diagnostic Accuracy and Efficiency. The diagnosis of language disorders associated with autism presents numerous challenges, including variability in symptom presentation and overlap with other developmental issues. Traditional diagnostic processes are often lengthy, subjective, and require extensive human effort, which may delay intervention. Utilizing ChatGPT, a state-of-the-art large language model, can enhance diagnostic accuracy and efficiency. This AI-powered approach can process natural language inputs at scale and identify nuanced patterns that human evaluators might miss. By integrating ChatGPT, clinicians can rapidly analyze language use patterns, thereby speeding up the diagnostic process and enabling earlier therapeutic interventions.
- Identification of Specific Linguistic Features. Current methods for identifying language disorders in autistic individuals primarily rely on general assessments that may not capture all the specific features relevant to the disorder. ChatGPT's capabilities include deep learning algorithms that excel in pattern recognition across large datasets. By exploiting these capabilities, the study aims to refine the profiling of language disorders by pinpointing distinct linguistic features most indicative of autism. These features include, but are not limited to, echolalia, pronoun reversal, and atypical use of language functions, which are critical for tailoring personalized treatment plans.
- Contribution to Personalized Medicine. Personalized medicine in ASD treatment plans is pivotal for effective intervention. By accurately diagnosing and specifically identifying the features of language disorders with ChatGPT, practitioners can better understand their patients' individual needs. This targeted approach not only improves outcomes but also aids in the development of personalized educational and therapeutic strategies. Furthermore, this research could pave the way for creating more sophisticated AI tools that can be adapted to other cognitive and developmental disorders, potentially revolutionizing the field of neurodevelopmental diagnostics.

2 Results

2.1 ChatGPT Model for ADOS Audio Dataset

We established the following computational framework:

Dataset. For the purpose of this study, we utilized the Caltech ADOS Audio Dataset, which comprises audio recordings from diagnostic interviews conducted under the ADOS-2, Module 4. This dataset includes recordings from 44 subjects diagnosed with ASD. Each subject participated in 15 different scenarios that are designed to elicit social and communicative behaviors characteristic of individuals on the autism spectrum.

Table 1 Performance Metrics of Different Models

Model	Accuracy	Precision	Recall	F1 Score
XLNet [20]	58.76%	54.38%	58.76%	56.07%
ALBERT [21]	69.07%	47.71%	69.07%	56.44%
DistilBERT [22]	58.76%	51.85%	58.76%	54.44%
RoBERTa [23]	57.73%	58.12%	57.73%	57.92%
BERT [15]	63.92%	60.86%	63.92%	61.87%
ChatGPT-based (Ours)	81.82%	82.45%	81.82%	79.89%

Table 2 Ablation Experiments: Performance Metrics of Different Schemes

Model	Accuracy	Precision	Recall	F1 Score
wo/ Speaker Diarization	63.64%	48.12%	63.64%	54.80%
w/ Pyannote	68.18%	59.68%	68.18%	60.45%
w/ Microsoft	72.73%	71.25%	72.73%	66.10%
w/ Google	81.82%	82.45%	81.82%	79.89%

Out of these scenarios, we specifically selected 11 that focus on social language interactions between the examiner and the patient. These selected scenarios provide a concentrated dataset to analyze social communicative exchanges, crucial for identifying language-related symptoms of ASD.

A4 Score and Labeling. The A4 score is a critical metric from the ADOS-2, Module 4, which assesses the "Stereotyped/Idiosyncratic Use of Words or Phrases." In our dataset: thirteen subjects had a score of 0, indicating minimal or no use of stereotyped language. Twenty-seven subjects had a score of 1, showing mild repetitive or formal use of language that is not obviously odd. Four subjects had a score of 2, frequently using stereotyped or odd phrases. For the purposes of this research, we combined the subjects with scores 1 and 2 into a single category (Category 1). Those with a score of 0 were grouped into Category 0. This categorization allowed us to simplify the binary classification task.

Evaluation Metrics. The effectiveness of the ChatGPT model was evaluated using several metrics: Accuracy: The proportion of total diagnoses that were correctly identified by the model. Precision: The ratio of correct positive observations to the total predicted positives. Recall (Sensitivity): The ratio of correct positive observations to the actual positives in the data. F1 Score: The harmonic mean of precision and recall, providing a single metric to assess the balance between precision and recall.

2.2 Comparison of Language Deficit Diagnosis

2.2.1 Evaluation of LLM Performance

In evaluating the effectiveness of various large language models for diagnosing language disorders associated with autism, we performed a comparative analysis focusing on several key performance metrics: accuracy, precision, recall, and F1 score. The models compared include XLNet, ALBERT, DistilBERT, RoBERTA, BERT, and our ChatGPT-based approach. Table 2 summarizes the results of this comparison.

Our ChatGPT-based model demonstrated superior performance across all metrics when compared to the other models. Specifically, ChatGPT achieved an accuracy of 81.82%, a precision of 82.45%, a recall of 81.82%, and an F1 score of 79.89%. This represents a significant improvement over the highest performing baseline model, BERT, which scored 63.92% in accuracy and 61.87% in F1 score. Notably, the improvements in accuracy and F1 score by our model were over 12% and 18% better than the BERT model, respectively. Therefore, the substantial gains in performance metrics underscore the effectiveness of the ChatGPT model in handling the nuances of language processing related to ASD. Accurately diagnosing SLD linked to ASD is essential for early intervention and effective treatment planning.

2.2.2 Evaluation of Speaker Diarization

To further examine the impact of utilizing speaker diarization, we conducted ablation experiments that varied the use of speaker diarization tools integrated with our ChatGPT-based approach:

The integration of Google's speaker diarization (SD) technology with our ChatGPT-based model (w/ Google) markedly enhanced all performance metrics, achieving the highest scores across the board. Unlike other diarization tools, Google SD not only distinguishes multiple speakers (e.g., Speaker 1, Speaker 2) but crucially identifies whether the speaker is the examiner or the patient. This capability is particularly beneficial for downstream tasks where understanding the interaction dynamics and the role of each speaker (examiner vs. patient) significantly influences the model's performance in contextual analysis and response generation.

Together, these results validate the potential of incorporating sophisticated AI-driven tools like speaker diarization with ChatGPT to enhance the accuracy and efficiency of diagnostics.

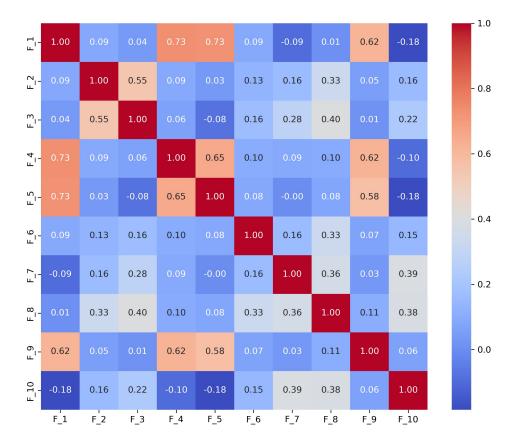


Fig. 1 Correlation Coefficients Between Features of Language Deficit

2.3 Analysis of Features of Language Deficit

2.3.1 Correlation Analysis

To thoroughly understand the interrelationships between different language features identified in the ASD diagnostic assessments, We analyzed the interrelationships among ten language features (F_1 to F_{10}) derived from the Caltech dataset. These features represent various aspects of language use that may indicate ASD, such as repetitive use of words or unusual language patterns. We calculated Pearson correlation coefficients between each pair of features to quantify their linear relationships. Each language feature is represented as a binary variable, where '1' indicates the presence and '0' indicates the absence of that specific language disorder feature within any given sample. For example, if a feature detected by ChatGPT such as "echolalic repetition" is observed in the dialogue during a diagnostic session, it is marked as '1' for that session; otherwise, it is marked as '0'. This binary coding allows us to apply Pearson correlation to measure the linear relationship between each pair of features across all samples. This analysis helps in pinpointing which features tend to cooccur within the linguistic profiles of ASD diagnosed through ADOS-2, Module 4. The computed correlation matrix for the features is presented in Figure 1. Detailed observations from Figure 1 are as follows:

1. Highly Correlated Features:

- F_1 , F_4 , and F_5 : These features show very high correlations (r = 0.734 between F_1 and F_4 , r = 0.727 between F_1 and F_5 , and r = 0.655 between F_4 and F_5). This suggests they may capture similar aspects of linguistic behavior, possibly related to the repetitive or stereotyped use of language, which is a common indicator of ASD.
- F_4 and F_9 : Another pair, F_4 and F_9 (r = 0.622), indicates a strong association, which might reflect overlapping features of language presentation in ASD, such as idiosyncratic language use or atypical language processing.

2. Moderately Correlated Features:

• F_2 and F_3 , F_8 and F_7 : These features exhibit moderate correlations (r = 0.549 for F_2 and F_3 , r = 0.363 for F_8 and F_7) that are significant but lower than those of F_1 , F_4 , and F_5 . They likely indicate a less direct but still meaningful relationship in linguistic traits, such as variability in speech that includes both repetitive and novel elements.

3. Negatively Correlated Features:

• F_1 and F_{10} : The negative correlation (r = -0.184) suggests that when F_1 (possibly denoting less severe ASD indicators) is present, F_{10} (perhaps denoting more severe ASD indicators) is less likely to be present, and vice versa. This can help differentiate levels of language impairment in ASD diagnoses.

Together, the exploration of the correlation between features of language deficit in ASD offers valuable insights into the complex nature of communication challenges faced by individuals on the spectrum.

2.3.2 Distribution of Features of Language Deficit Across Scenarios

This subsection analyzes the correlations between linguistic features across various ADOS scenarios to identify patterns that may indicate language disorders associated with ASD. The focus is on scenarios that involve direct dialogue between the examiner and the patient, reflecting our study's emphasis on communicative interactions. While Scenarios S_1 , S_2 , S_8 , and S_{10} provide valuable insights into various aspects of cognitive and social functioning, they were not included in this analysis due to their lack of direct dialogue-based interaction between the examiner and the patient, which is a primary focus of our research. To effectively analyze the differences in the distribution of values from F_1 to F_{10} across various scenarios, we conducted a detailed statistical examination (see Table 3). This analysis helps to understand how the prevalence of each linguistic feature associated with ASD varies across the scenarios, which can provide insights into the contexts or conditions under which certain features are more likely to appear.

Table 3 Prevalence of Linguistic Features by Scenario Indicative of Language Deficits in ASD

Scenario	3	4	5	6	7	9	11	12	13	14	15
F_1	0.87	0.00	0.00	0.00	0.00	0.77	0.00	0.00	0.00	0.00	0.63
F_2	0.90	0.81	0.81	0.87	0.84	0.81	0.77	0.94	0.77	0.80	0.90
F_3	0.81	0.74	0.81	0.90	0.77	0.61	0.77	0.81	0.53	0.67	0.50
F_4	0.68	0.00	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.50
F_5	0.61	0.00	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.67
F_6	0.94	0.90	0.74	0.90	0.81	0.77	0.81	0.84	0.83	0.87	0.93
F_7	0.77	0.77	0.87	0.87	0.97	0.74	0.90	0.90	0.80	0.63	0.70
F_8	0.71	0.65	0.65	0.74	0.77	0.48	0.68	0.74	0.63	0.50	0.57
F_9	0.61	0.00	0.00	0.00	0.00	0.42	0.00	0.00	0.00	0.00	0.43
F_{10}	0.71	0.77	0.74	0.81	0.90	0.42	0.81	0.90	0.63	0.57	0.50

We have derived the following observations and insights:

- Feature Prevalence: The occurrence rates of features F_2 , F_6 , and F_7 , which represent aspects of unconventional content, verbal fluency, and excessive social phrasing respectively, were consistently above 60% across most scenarios. This high prevalence underscores their significance as key indicators of ASD.
- Language Feature in Social Contexts: Features such as F_1 (possibly related to echolalia or repetitive speech), F_4 , F_5 , and F_9 (potentially related to atypical or stereotyped language use) were entirely absent in several scenarios, underscoring their sensitivity to specific social or communicative contexts.
- Scenario-Specific Patterns: High prevalence rates in F_7 during the S_7 (i.e., 'Emotions') scenario, and diverse responses in F_2 across the S_{12} (i.e., 'Friends, Relationships, and Marriage') and S_{15} (i.e., 'Creating a Story') scenarios suggest that certain linguistic features were particularly elicited by emotional or social relational contexts.

To further demonstrate the utility of this analysis, we specifically focused on the S_3 and S_9 scenarios, which are essential for evaluating narrative skills and abstract reasoning, respectively. We derived the following results:

• Scenario S_3 (Figure 2): The strong correlation between F_1 and F_6 (0.68) indicates challenges in effectively summarizing visual content. This may reflect difficulties in processing and conveying information succinctly, which is often a challenge for individuals with ASD. A high correlations (0.66) between F_8 (monotone social expression) and F_9 (stereotyped media quoting) suggests that individuals may struggle with varying their emotional expressions, which could affect the emotional richness of their speech. Correlations between F_7 (excessive social phrasing) and F_4 (incongruous humor) (0.62), and between F_7 and F_9 unconventional content (0.61) suggest a connection between repetitive social expressions and the production of either

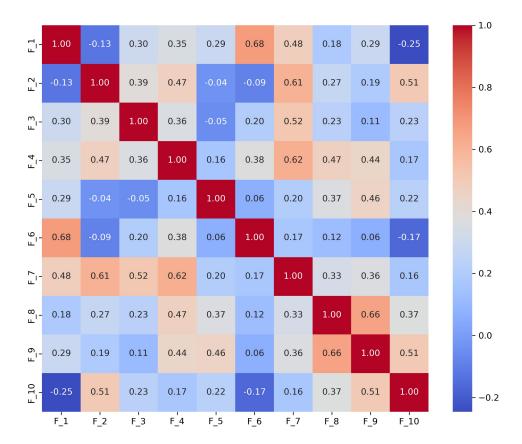


Fig. 2 Correlation matrix of linguistic features F_1 to F_{10} in the S_3 (i.e., 'Description of a Picture') scenario. The matrix shows strong correlations between features, underscoring the interdependencies that influence how visual information is described.

inappropriate humor or atypical content. This pattern may indicate that individuals with ASD use scripted language as a strategy to manage social interactions, although this can often result in conversations that seem awkward or misplaced.

• Scenario S_9 (Figure 3): The strong correlation between F_2 and F_3 (0.62) suggest that individuals with ASD might struggle to adjust their language to fit the context appropriately. This is particularly problematic in scenarios like watching and discussing cartoons, where understanding shifting dialogues and multiple characters' perspectives is essential; Additionally, F_8 's significant correlations with F_7 (0.57) reflects difficulties in varying emotional tone and using phrases that might be socially appropriate. Individuals exhibiting these features tend to speak in a flat, unmodulated manner while possibly overusing certain social phrases, making their speech seem rigid and scripted. Such speech patterns can make it difficult for them to engage in spontaneous and emotionally responsive interactions, which are critical for successful social exchanges.

Together, these correlations suggest co-morbid linguistic challenges that individuals with ASD may encounter in scenarios requiring detailed visual interpretation or complex narrative understanding.

2.4 Case Study

Lastly, we present two case studies to illustrate the practical application of ChatGPT in identifying language deficits in ASD.

Table 4 and 5 show the dialogue between an examiner (E) and a patient (P). It showcases typical conversational challenges faced by individuals with ASD. The patient's responses highlight several linguistic features that indicate underlying language disorders.

Together, these case studies demonstrate the effectiveness of using ChatGPT, combined with structured conversational analysis, to diagnose social language disorders in ASD. The identified features align well with known ASD communication challenges, providing a robust basis for further diagnostic evaluation and intervention planning.

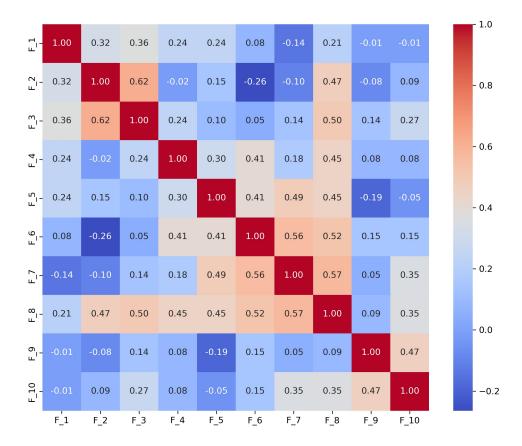


Fig. 3 Correlation matrix of linguistic features F_1 to F_{10} in the S_9 (i.e., 'Cartoons') scenario. This matrix highlights correlations that elucidate the cognitive and perceptual challenges in interpreting cartoons, essential for understanding narrative contexts and humor in ASD.

3 Discussion

This study leveraged the ChatGPT model augmented with Google's speaker diarization and transcription technologies to analyze language patterns in the Caltech ADOS Audio Dataset. The dataset included audio recordings from 44 adults diagnosed with ASD, focusing on scenarios that elicit social language interactions critical for diagnosing language-related symptoms of ASD. The incorporation of ChatGPT significantly enhanced the diagnostic process, yielding superior performance metrics compared to other models like BERT [15], RoBERTa [23], and XLNet [20], particularly in terms of accuracy, precision, recall, and F1 score.

One of the most significant outcomes of this study is the improved capability of ChatGPT to recognize and understand nuanced language deficits, which are often subtle and complex in adults with ASD. The model's advanced analytical abilities allowed for a deeper examination of speech patterns and linguistic anomalies that traditional methods might miss. Our study complements the recent study of large language models (LLM) for encoding clinical knowledge [24]. Note that our current understanding of ASD from a clinical perspective is still limited. We expect that LLM such as ChatGPT might help enrich or expand clinical knowledge from clinical data in the future.

This enhanced detection is crucial, as it enables clinicians to diagnose more accurately and also contributes to a better understanding of the linguistic challenges faced by individuals with ASD. Our effort is well aligned with the existing project of building language resources for ASD [25]. Particularly, the use of Google's speaker diarization technology has proven essential in accurately identifying the speaker roles (examiner vs. patient), which significantly impacts the model's ability to analyze dialogue effectively. This synergy not only enhances diagnostic accuracy but also enriches the data quality with well-attributed, contextually segmented transcripts, facilitating more detailed and precise language analysis.

The results from the present study have strong clinical implications. Our model's ability to dissect complex language interactions and identify nuanced language use offers a profound advantage in clinical settings. It allows for an earlier and more accurate detection of language deficits, which are often indicative of ASD. This

Table 4 Case Study Analysis: Identifying Language Deficits in an Examiner-Patient Dialogue. Phrases highlighted in blue indicate observed linguistic anomalies, while red underscores the specific feature category of language deficits.

```
E: Okay. So, do you have some friends?
P: Uh, do I have some friends? F_1
E: Um-hum.
P: Well, pretty \operatorname{much}_{F_{10}}, three of them from peers.
E: Three of them from here?
P: Um-hum.
E: Okay. Can you tell me a little bit about them?
P: Well, they're kind of living near, they kind of live near her_{F_2} farther from here.
E: They're further from here? What do they like?
P: What do they like?F_1 They're kind of energetic, just like me. Cool.
E: Um, and what do you guys like to do together? Man, we like movies and stuff.
P: And you've got to know them through peers.
E: And, but you said you'd go, you'd like to go to movies and stuff as well. Do you go to movies with them, or?
P: We use gas movies_{F_9}.
E: Oh, you talk about it?
P: Yeah.
E: Okay. And are there people outside of peers that you're friends with, or?
P: You mean, uh, outside of peers_{F_1}?
P: Crazy, crowded, crooked.. One of those years people.
E: Oh.
P: They triggered the trip, pregnant sound effects. F_0
E: Oh. veah.
P: When they asked about dating.. Um What, where do you, uh, want to live when you get older
E: face?
                                      a lounge and dirty autistic matching F_2.
P:
          want
                   to
                        live
                               in
                                                                                     You
                                                                                             know,
                                                                                                      you
                                                                                                              can
zillion blocks matching_{F_{10}}.
E: And who do you think you would like to live with, with your family or roommates or by yourself?
P: I want to live with my family there. Okay
```

Extracted Features Based on ChatGPT Response

Examiner (E) - Patient(P) Dialogue

Echoic Repetition (F_1) : When the examiner first asked the patient whether they have some friends, the patient echoed the question back at the examiner before answering. In subsequent interactions, the patient frequently mimics the examiner's questions verbatim before answering.

Unconventional Content (F_2) : The patient refers to living in "a lounge and dirty autistic matching" rather than using any conventional descriptions for living spaces. Similarly, the phrase "zillion blocks matching" has an unusual content.

Pronoun Displacement (F_3) : The patient referred to his own house as "her".

Stereotyped Media Quoting (F_9) : The patient quoted "gas movies" and "triggered the trip, pregnant sound effects", which seems to be quoted from an external media source.

Clichéd Verbal Substitutions (F_{10}): The patient uses clichéd expressions like "well, pretty much" instead of giving direct responses.

early diagnosis is crucial for the timely intervention that can lead to better management and outcomes for adults with ASD. A promising future direction is to leverage the power of LLM into distinguishing ASD from other language impairment during the development [26]. If LLM can shed new insight to the co-occurrence of ASD and language impairment, clinical diagnosis of developmental disorders might benefit from human-AI collaboration.

Despite its innovations, this study has limitations that should be addressed in future research. The effectiveness of the ChatGPT model depends heavily on the quality and variety of the training data. The current dataset, while substantial, represents a relatively homogeneous population in terms of linguistic and cultural backgrounds. Expanding the dataset to include a more diverse population could help improve the model's robustness and generalizability. Furthermore, future studies could explore the integration of multimodal data analysis [27] to enhance diagnostic capabilities further. Combining speech with visual cues such as facial expressions and body language could provide a more comprehensive view of an individual's communicative and social behaviors. Additionally, refining the models to incorporate feedback loops that allow continual learning from new data can adaptively improve their diagnostic accuracy over time [28].

4 Methods

4.1 Evaluating Autism in Adults: The ADOS-2 Module 4 Diagnostic Process

The ADOS-2 [29, 30] is an update and extension of the original ADOS, which is a standardized diagnostic tool for ASD. The ADOS assesses communication, social interaction, play, and restricted and repetitive behaviors. It provides a series of structured and semi-structured tasks that involve social interactions between the

Table 5 Case Study Analysis: Identifying Language Deficits in an Examiner-Patient Dialogue. Phrases highlighted in blue indicate observed linguistic anomalies, while red underscores the specific feature category of language deficits.

Examiner (E) - Patient(P) Dialogue

E: So, I'm going to ask you a few questions about work and school

P: Yes.

E: Um, first of all, do you have a job?

P: No, I used to be laid off.

E: And that's okay? Yeah Um, while you were working or now at school, or at high school, maybe before that, did you have a group of, any problems getting along with people You weren't in high school?

P: Any school. Well, like, like, stupid schools for you when I was developing angry or high school. F_2

E: What kind of things you used to bother you that other people did?

P: Like, uh, when I was in the school bus I had students grabbing my backpack, whatever, and I didn't mad it or $suck._{F_{10}}$

...

E: And have you ever done anything so that other people wouldn't teach soon?

P: Yes, but sometimes they just, it's like they've been doing it for a while, so it's just kind of like Hey, you know or what, whatever, F_6 we'll just tease him about something else.

...

Extracted Features Based on ChatGPT Response

Unconventional Content (F_2) : There are instances where the patient uses unconventionally chosen phrases like "stupid schools for you when I was developing angry or high school".

Superfluous Phrase Attachment (F_6): The patient attaches redundant phrases or filler expressions to their speech without contributing any substantive meaning or context, such as 'whatever' and 'or whatever'.

Clichéd Verbal Substitutions (F_{10}): The patient resorts to clichéd expressions when describing how he felt during certain situations: "I didn't mad it or suck.

Scenario	Name	Explanation
S_1	Construction Task	Involves the participant engaging in a task that requires
		constructing or assembling a set structure, testing spatial
		and motor skills rather than communicative abilities.
S_2	Telling a Story from a Book	Primarily a monologic task where the participant recounts
		a story from a book, differing from spontaneous dialogic
- C	D i i i G Di i	interactions.
S_3	Description of a Picture	Participants describe a picture, testing their ability to
		interpret visual information and articulate a coherent
S_4	Conversation and Reporting	description. Focuses on the ability to engage in back-and-forth conver-
54	Conversation and Reporting	sation and to report on past events.
S_5	Current Work and School	Discusses participants' current educational and occupa-
25	Current Work and School	tional engagements.
S_6	Social Difficulties and Annoy-	Elicits experiences of social challenges and annoyances.
	ance	
S_7	Emotions	Requires participants to express and identify emotions.
S_8	Demonstration Task	Requires the participant to demonstrate how to use an
		item or explain a process, which does not involve interac-
		tive communication with an examiner.
S_9	Cartoons	Involves interpreting sequences and explaining cartoon
- C	D. I	strips.
S_{10}	Break	A pause or intermission in the assessment, involving no
C	Daily Living	communicative or cognitive tasks. Covers daily routines and personal care tasks.
$\frac{S_{11}}{S_{12}}$	Friends, Relationships, and	Discusses personal relationships and social norms regard-
512	Marriage	ing friendships and marital status.
S_{13}	Loneliness	Addresses feelings and situations of loneliness and isola-
~13	Londinobb	tion.
S_{14}	Plans and Hopes	Involves discussing future aspirations and plans.
S_{15}	Creating a Story	Tests creative storytelling abilities in an unstructured
		task.

 ${\bf Table~6~~Overview~of~Scenario~Tasks~in~ADOS-2~Module~4~Diagnosing~process}$

examiner and the person being assessed. Module 4 of the ADOS-2 is designed for verbally fluent adolescents and adults (see Table 6 for description of tasks). In addition, Module 4 of the ADOS-2 organizes observations into five main areas, assessing various aspects of interaction and communication critical for diagnosing ASD in verbally fluent adolescents and adults. Table 7 provides a summary of these categories, including the specific items they encompass and their respective descriptions: each participating in 15 different scenarios (see Table 6) designed to elicit communicative and social responses that are indicators of ASD. The scenarios were structured to cover a comprehensive range of social interactions and communicative behaviors.

Table 7 Detailed Assessment Categories for the ADOS-2 Module 4 Observations

Class	Name	Item	ıs	Description
A	Language and	A1	\sim	Assesses the ability to use speech and gestures in commu-
	Communica-	A10		nication effectively, evaluating the clarity, coherence, and
	tion			appropriateness of language used in social interactions.
В	Reciprocal	B1	\sim	Focuses on non-verbal and verbal behaviors used in social
	Social Interac-	B13		interactions, including eye contact, facial expressions,
	tion			body postures, and the quality of speech interactions.
С	Imagination /	C1		Evaluates the subject's ability to use imagination and
	Creativity			creativity in their expressions and thoughts, such as sto-
				rytelling or creating novel responses to social scenarios.
D	Stereotyped	D1	\sim	Includes specific behaviors that are repetitive, restricted,
	Behaviors and	D5		and stereotyped. This category assesses the frequency and
	Restricted			intensity of these behaviors as indicators of ASD.
	Interests			
E	Other Abnor-	E1	~	Observes behaviors that are typically considered abnor-
	mal Behaviors	E3		mal, such as overactivity, anxiety, and emotional responses
				that are inconsistent with the normative context.

In language-based diagnostics, the **A4 score** — part of the Stereotyped Behaviors and Restricted Interests category — becomes particularly relevant. This score assesses:

- 0 = "Rarely or never uses stereotyped or idiosyncratic words or phrases."
- 1 = "Use of words or phrases tends to be more repetitive or formal than that of most individuals at the same level of expressive language, but not obviously odd, OR occasional stereotyped utterances or odd use of words or phrases, with substantial spontaneous, flexible language as well."
- 2 = "Often uses stereotyped utterances or odd words or phrases, with some other language."
- 3 = "Frequently uses odd or stereotyped speech, and rarely uses non-stereotyped spontaneous speech."

The A4 score assesses the use of stereotyped language, which is a critical indicator of ASD. A higher A4 score suggests a more frequent use of stereotyped or idiosyncratic speech, aiding in the diagnosis of ASD with higher specificity and sensitivity.

4.2 Framework for Diagnosing Autism and Identifying Language Disorders

Building on the foundational practices established by the ADOS-2, specifically Module 4 designed for verbally fluent adolescents and adults, we have developed a comprehensive framework (see Figure 4) that incorporates LLMs like ChatGPT. This framework is tailored to enhance the diagnostic precision and identification of language disorders in individuals suspected of having ASD. Specifically, it involves the following components:

- Speaker Diarization and Audio Transcription. This technology segments the audio recordings to precisely separate the speech of the examiner from that of the patient. Such separation is crucial as it enhances the understanding of the patient's behavior in conversational contexts by isolating their verbal responses, which are then analyzed for potential linguistic abnormalities. The audio segments identified through diarization are subsequently transcribed into text using Google's state-of-the-art transcription technologies (see Table 4). This conversion facilitates a detailed examination of the social language used by the patient, aiding in the detection of disorder-specific features within their speech.
- Language Pattern Analysis Using ChatGPT. In this framework, ChatGPT is utilized not only to diagnose ASD but also to identify specific language disorder characteristics that are indicative of ASD. The process begins with the preparation of structured prompts that are designed to elicit comprehensive information from the dialogues between examiners and patients. These prompts are crafted as follows:
 - Examiner-Patient Dialogue (EPD): The dialogue text, which includes conversational exchanges between the examiner and the patient, serves as the primary input for ChatGPT. This dialogue is carefully processed to maintain the integrity and context of the interaction, ensuring that all relevant linguistic cues are preserved.
 - Question Design: To guide the analysis, specific questions are formulated based on the dialogue content.
 These questions aim to direct ChatGPT's attention to potential signs of language disorders, such as repetitive phrasing, atypical language use, or disrupted conversational flow.
 - Knowledge Design: This component incorporates domain-specific knowledge from autism diagnostics, which is used to refine ChatGPT's responses. By integrating expert knowledge, the model is better equipped to recognize and interpret the subtle nuances that characterize ASD-related language disorders.
 - Prompt Integration: The complete prompt for ChatGPT includes the dialogue text, the targeted questions, and the expert knowledge cues. This integrated approach helps in precisely pinpointing disorder characteristics that might be overlooked in a less structured analysis.

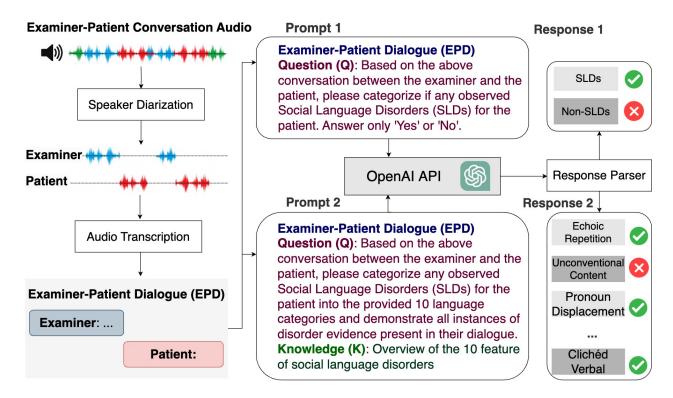


Fig. 4 Framework for Diagnosing Autism and Identifying Language Disorders

- Functionality of the Response Parser: The response parser is a critical element that processes the outputs from ChatGPT. It performs two main functions:
 - Diagnosis of Language Disorders: It evaluates ChatGPT's responses to identify language disorders in each scenario task. If a disorder is present in any task, the subject is predicted to have a language disorder associated with ASD. It categorizes these disorders based on predefined criteria that reflect typical ASD manifestations in language.
 - Identification of Specific Characteristics: Beyond mere diagnosis, the response parser also identifies
 specific characteristics of the language disorders. It extracts detailed information about the nature and
 extent of the linguistic anomalies detected, such as the type of stereotypy or idiosyncrasy in the patient's
 speech.

4.3 Examiner-Patient Audio Separation Based on Speaker Diarization

This subsection details the utilization of Google's advanced audio analysis tools to implement speaker diarization and audio transcription, facilitating the effective separation of examiner and patient speech in audio recordings. This technology is pivotal for analyzing communicative interactions in our study, which focuses on identifying language disorders associated with ASD.

Speaker diarization is the process of partitioning an audio stream into homogeneous segments according to the identity of the speaker. It involves distinguishing speakers in an audio recording and attributing speech segments to those individual speakers without prior knowledge of their identities. This process is crucial for scenarios where understanding the dialogue structure and dynamics between multiple speakers (such as an examiner and a patient) is essential. Our choice of Google's technology for speaker diarization and transcription was driven by its superior capability to recognize and label speakers based on the diagnosis scene contextually. Unlike other technologies, such as Microsoft's, which generally label speakers numerically (e.g., Speaker 1, Speaker 2) without any context of their roles, Google's tools can accurately identify and distinguish roles (e.g., Examiner, Patient) within the conversation. This functionality is crucial for our assessments as it allows for a precise analysis of the dialogues in terms of who is speaking, enhancing the contextuality and relevance of the linguistic data extracted.

We employed the following steps: 1. Audio Segmentation: Each audio recording, typically longer than one hour per subject, is segmented based on the scenario (e.g., describing a picture, interpreting cartoons). This targeted segmentation helps isolate the conversations relevant to specific assessment tasks, making them more manageable and focused for analysis. 2. Model Configuration: The Medical-Conversation model setting is used to recognize and differentiate between two primary speakers, typically the 'Examiner' and the 'Patient', within a medical or diagnostic context. By configuring the transcription service to recognize these roles specifically, we ensure that the transcription outputs are accurately labeled, reflecting the dialogue true

dynamic. 3. Speaker Diarization and Speech-to-Text Transcription: Applying Google's diarization algorithm, each segmented audio file is processed to identify and label the speakers' voices throughout the conversation. Following the diarization, the speech-to-text transcription is executed on these segmented files. This process guarantees that each speaker's contributions are correctly identified and transcribed, providing a reliable textual basis for subsequent linguistic analysis.

4.4 Diagnosing Language Disorders Associated with Autism via ChatGPT

This subsection details the methodology used to employ ChatGPT, an advanced language model, for diagnosing Social Language Disorders (SLDs) in individuals with ASD. The approach leverages a structured prompt to analyze dialogues between examiners and patients, determining the presence of communicative impairments characteristic of ASD.

Prompt Design for ChatGPT: This process involved parts. In Part 1, Examiner-Patient Dialogue (EPD), the input to ChatGPT included the transcribed dialogue between the examiner and the patient, presenting the conversational context needed for assessment. In Part 2, Question (Q), following the dialogue, ChatGPT was asked: "Based on the above conversation between the examiner and the patient, please categorize if any observed SLDs for the patient. Answer only 'Yes' or 'No'." This question aimed to elicit a definitive response based on the dialogue's content, focusing solely on the presence or absence of disorder indicators.

Response Interpretation Using ChatGPT: The responses from ChatGPT were parsed to determine the presence of SLDs. The decision process was as follows:

- Response Parser: Each response from ChatGPT, indicating either affirmation ("Yes") or negation ("No"), was analyzed to ascertain whether the patient exhibited symptoms of SLDs based on the dialogue provided. The parser specifically looked for expressions of affirmation or negation concerning the presence of communicative impairments.
- Diagnosis Determination: For each subject, a diagnosis of a SLD was considered positive if there was at least one scenario where ChatGPT affirmed the presence of SLDs ("Yes"). Conversely, if all scenarios resulted in a "No" from ChatGPT, the subject was not considered to have SLDs as per the dialogues analyzed.

Significance of This Approach: Utilizing ChatGPT for this purpose offers several advantages:

- Scalability: The ability to process large volumes of dialogue data quickly and uniformly without human interviewer bias.
- Consistency: Standardized prompt responses ensure that the assessment criteria remain constant across all examinations.
- **Precision:** Advanced natural language understanding allows ChatGPT to detect subtle nuances in dialogue that may indicate disorders, which are often challenging for human evaluators to perceive consistently.

By integrating ChatGPT's advanced analytical capabilities, this methodology refines the diagnostic process for social language disorders in ASD, enhancing both the efficiency and accuracy of assessments. This approach not only supports clinicians by providing a reliable diagnostic tool but also contributes to the broader field of psycholinguistics by offering insights into the communicative impairments often seen in ASD.

4.5 Identifying Language Disorder Features Associated with ASD via ChatGPT

This subsection elaborates on the methodology employed to harness ChatGPT for identifying specific language disorder features associated with ASD, guided by expert knowledge integrated from the ADOS-2, Module 4. The approach utilizes a comprehensive list of language disorders designed around the nuanced communication requirements and symptoms observed in verbally fluent adolescents and adults.

4.5.1 Autism-Associated Language Disorders features

Based on the domain knowledge of professional ADOS-2 examiners, ten specific features of language deficits related to ASD have been identified. These features reflect various unconventional use patterns of language that can signify underlying social communication issues. Table 8 is a detailed description of these features:

4.5.2 ChatGPT Prompt Design for Feature Extraction

To facilitate the extraction of these features of language deficits using ChatGPT, a specific prompt structure is utilized, as shown in 'Prompt 2' (Figure 4). The prompt was organized into three parts to optimize the analysis, including Part 1: Examiner-Patient Dialogue (EPD), Part 2: Question (Q) - ..., and Part 3: Knowledge (K) - "Overview of the 10 features of social language disorders identified by ADOS-2 examiners, as shown in the column 'Explanation' in Table 8

F	Name	Explanation
F_1	Echoic Repetition	The individual mimics verbatim what has been said by others, including the examiner, or recites phrases from external sources like advertisements or movie scripts, showing a delayed echo response.
F_2	Unconventional Content	The speech contains peculiarly chosen content or contextually odd phrasing, such as using 'unfreshness through household' for lack of novelty, 'mideast' instead of 'midwest' for U.S. states, or describing entry into a building as 'through various apertures'.
F_3	Pronoun Displacement	Incorrectly substitutes personal pronouns, using 'you' in place of 'I', or refers to themselves in the third person, either by pronouns like 'he/she' or by their own name.
F_4	Incongruous Humor Timing	Incorporates humorous or comedic expressions inappropriately during discussions meant to be serious, showing a misalignment between the content's emotional tone and the context.
F_5	Formalistic Language Use	Employs an overly formal or archaic language style that seems lifted from written texts, legal documents, or old literature, rather than engaging in conversational speech. Examples include elaborate ways of expressing simple ideas or feelings.
F_6	Superfluous Phrase Attachment	Attaches redundant phrases or filler expressions to their speech without contributing any substantive meaning or context, such as 'you know what I mean' or 'as they say,' indicating a habit rather than intentional emphasis.
F_7	Excessive Social Phrasing	Utilizes conventional social expressions excessively or inappropriately, responding with phrases like 'oh, thank you' in contexts where it does not fit or preempting social gestures not yet performed by the interlocutor.
F_8	Monotone Social Expression	Reiterates social phrases with an unchanged, monotonous intonation, indicating a lack of genuine emotional engagement or variability in social interactions.
F_9	Stereotyped Media Quoting	Quotes lines from commercials, movies, or TV shows in a highly stereotypical manner, employing a canned intonation that mimics the original source closely, suggesting a reliance on external media for verbal expressions.
F_{10}	Clichéd Verbal Substitutions	Resorts to well-known sayings or clichés in lieu of engaging in direct conversational responses, using phrases like 'circle of life' or 'ready to roll' as stand-ins for more personalized communication.

Table 8 Descriptive Analysis of Unconventional Language Disorder Patterns

This structured prompt design guides ChatGPT to analyze the transcribed conversations and categorize language deficits, enhancing the precision of diagnostics based on observed linguistic patterns.

Response Interpretation Using ChatGPT: ChatGPT's responses were analyzed to determine the presence and types of SLD features as follows:

- Response Parser: The parser reviewed ChatGPT's responses, which involved multiple labels corresponding to the 10 predefined SLD features. Each piece of dialogue could yield several labels, reflecting the multi-dimensional nature of language disorders.
- Feature Classification: Each response was predicted into multiple categories, constituting a multi-label classification task. This approach allowed for a comprehensive assessment of the patient's language abilities, identifying multiple SLD features from a single excerpt of dialogue.

Significance of This Multi-Label Classification Approach:

- Comprehensive Analysis: By classifying dialogue into multiple SLD categories, ChatGPT provides a nuanced view of the patient's communicative impairments, offering detailed insights that are critical for accurate diagnosis.
- Targeted Interventions: Identifying specific disorder features allows clinicians to design more focused and effective intervention strategies, tailored to address the distinct challenges faced by the patient.

Utilizing ChatGPT to identify and classify language disorder features via a structured multi-label classification approach significantly refines the diagnostic capabilities in ASD assessments. This methodology not only enhances the accuracy of the diagnoses but also deepens the understanding of the patient's specific communicative deficits, facilitating the development of targeted therapeutic strategies.

5 Conclusion

This research confirmed the substantial benefits of integrating LLMs such as ChatGPT with the ADOS-2 procedures for diagnosing ASD in adults. Utilizing ChatGPT, enhanced with Google's speaker diarization and transcription technologies, significantly improved the accuracy, precision, recall, and F1 score of language deficit diagnoses compared to traditional models. This integration not only streamlines the diagnostic process, making it more efficient and less subjective but also enhances the scalability of interventions, providing faster and more accurate assessments that are crucial for effective treatment planning.

Looking forward, the study highlights the potential for these technologies to incorporate a wider variety of data and to develop adaptive learning models that continually improve in accuracy and effectiveness. This progression promises to revolutionize ASD diagnostics, paving the way for more personalized and accessible care for individuals with ASD. The integration of LLMs like ChatGPT in clinical settings is a forward step in making ASD diagnostics not only quicker and more accurate but also more comprehensive in understanding and addressing the diverse needs of the autism community.

Declarations

- Funding
 - This research was supported by the NSF (IIS-2114644) and NIH (R01MH129426). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.
- Conflict of interest/Competing interests (check journal-specific guidelines for which heading to use) The authors declare no conflict of interest.
- Author contribution
 - C.H., L.K.P., S.W., X.L. designed research. L.K.P. performed experiments. C.H., W.L., M.R., and X.Y. analyzed data. C.H., S.W., and X.L. wrote the paper. All authors discussed the results and contributed toward the manuscript.

References

- [1] Leekam, S.R., Prior, M.R., Uljarevic, M.: Restricted and repetitive behaviors in autism spectrum disorders: a review of research in the last decade. Psychological bulletin 137(4), 562 (2011)
- [2] Lord, C., Elsabbagh, M., Baird, G., Veenstra-Vanderweele, J.: Autism spectrum disorder. The lancet 392(10146), 508–520 (2018)
- [3] Lord, C., Brugha, T.S., Charman, T., Cusack, J., Dumas, G., Frazier, T., Jones, E.J., Jones, R.M., Pickles, A., State, M.W., et al.: Autism spectrum disorder. Nature reviews Disease primers 6(1), 1–23 (2020)
- [4] Lauritsen, M.B.: Autism spectrum disorders. European child & adolescent psychiatry 22, 37–42 (2013)
- [5] Baird, G., Norbury, C.F.: Social (pragmatic) communication disorders and autism spectrum disorder. Archives of Disease in Childhood **101**(8), 745–751 (2016)
- [6] Nazeer, A., Ghaziuddin, M.: Autism spectrum disorders: clinical features and diagnosis. Pediatric Clinics 59(1), 19–25 (2012)
- [7] Sperry, L.A., Mesibov, G.B.: Perceptions of social challenges of adults with autism spectrum disorder. Autism 9(4), 362–376 (2005)
- [8] Velikonja, T., Fett, A.-K., Velthorst, E.: Patterns of nonsocial and social cognitive functioning in adults with autism spectrum disorder: A systematic review and meta-analysis. JAMA psychiatry **76**(2), 135–151 (2019)
- [9] Rapin, I., Dunn, M.: Update on the language disorders of individuals on the autistic spectrum. Brain and development 25(3), 166–172 (2003)
- [10] Magiati, I., Tay, X.W., Howlin, P.: Cognitive, language, social and behavioural outcomes in adults with autism spectrum disorders: A systematic review of longitudinal follow-up studies in adulthood. Clinical psychology review **34**(1), 73–86 (2014)

- [11] Whitehouse, A.J., Watt, H.J., Line, E., Bishop, D.V.: Adult psychosocial outcomes of children with specific language impairment, pragmatic language impairment and autism. International journal of language & communication disorders 44(4), 511–528 (2009)
- [12] Lord, C., Rutter, M., Goode, S., Heemsbergen, J., Jordan, H., Mawhood, L., Schopler, E.: Autism diagnostic observation schedule. Journal of Autism and Developmental Disorders (2012)
- [13] Thirunavukarasu, A.J., Ting, D.S.J., Elangovan, K., Gutierrez, L., Tan, T.F., Ting, D.S.W.: Large language models in medicine. Nature medicine **29**(8), 1930–1940 (2023)
- [14] Yang, X., Chen, A., PourNejatian, N., Shin, H.C., Smith, K.E., Parisien, C., Compas, C., Martin, C., Costa, A.B., Flores, M.G., et al.: A large language model for electronic health records. NPJ digital medicine 5(1), 194 (2022)
- [15] Devlin, J., Chang, M.-W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)
- [16] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al.: Language models are few-shot learners. Advances in neural information processing systems 33, 1877–1901 (2020)
- [17] Kapp, S.K., Steward, R., Crane, L., Elliott, D., Elphick, C., Pellicano, E., Russell, G.: 'people should be allowed to do what they like': Autistic adults' views and experiences of stimming. Autism 23(7), 1782–1792 (2019)
- [18] Ellis Weismer, S., Lord, C., Esler, A.: Early language patterns of toddlers on the autism spectrum compared to toddlers with developmental delay. Journal of autism and developmental disorders 40, 1259–1273 (2010)
- [19] Provost, B., Lopez, B.R., Heimerl, S.: A comparison of motor delays in young children: autism spectrum disorder, developmental delay, and developmental concerns. Journal of autism and developmental disorders 37, 321–328 (2007)
- [20] Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R.R., Le, Q.V.: Xlnet: Generalized autore-gressive pretraining for language understanding. Advances in neural information processing systems **32** (2019)
- [21] Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., Soricut, R.: Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942 (2019)
- [22] Sanh, V., Debut, L., Chaumond, J., Wolf, T.: Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108 (2019)
- [23] Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V.: Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692 (2019)
- [24] Singhal, K., Azizi, S., Tu, T., Mahdavi, S.S., Wei, J., Chung, H.W., Scales, N., Tanwani, A., Cole-Lewis, H., Pfohl, S., et al.: Large language models encode clinical knowledge. Nature **620**(7972), 172–180 (2023)
- [25] Parish-Morris, J., Cieri, C., Liberman, M., Bateman, L., Ferguson, E., Schultz, R.T.: Building language resources for exploring autism spectrum disorders. In: LREC... International Conference on Language Resources & Evaluation:[proceedings]. International Conference on Language Resources and Evaluation, vol. 2016, p. 2100 (2016). NIH Public Access
- [26] Loucas, T., Charman, T., Pickles, A., Simonoff, E., Chandler, S., Meldrum, D., Baird, G.: Autistic symptomatology and language ability in autism spectrum disorder and specific language impairment. Journal of Child Psychology and Psychiatry 49(11), 1184–1192 (2008)
- [27] Han, J., Jiang, G., Ouyang, G., Li, X.: A multimodal approach for identifying autism spectrum disorders in children. IEEE Transactions on Neural Systems and Rehabilitation Engineering **30**, 2003–2011 (2022)
- [28] Biesialska, M., Biesialska, K., Costa-Jussa, M.R.: Continual lifelong learning in natural language processing: A survey. arXiv preprint arXiv:2012.09823 (2020)

- [29] Lord, C., Rutter, M., DiLavore, P.C., Risi, S., Gotham, K., Bishop, S.L., et al.: Ados. Autism diagnostic observation schedule. Manual. Los Angeles: WPS (1999)
- [30] American Psychiatric Association, D., Association, A.P., et al.: Diagnostic and Statistical Manual of Mental Disorders: DSM-5 vol. 5. American psychiatric association Washington, DC, ??? (2013)