Are You F*$king Kidding Me? Autistic Lack of Representation in Social Robotic Large Language Model Designs

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Abstract

There is a need for diverse and inclusive speech datasets (Abbo et al., 2025; Ganguli et al., 2022; 2023). Recent calls from UNESCO regarding concerns for stereotypical identities (Dennler et al., 2025) match recent studies quests for diverse speech datasets (He et al., 2024). Large Language Models (LLMs) are used to encourage adaptability between robot and users. A review of human-robot interaction (HRI) studies (Rizvi et al., 2024) found that autistic individuals, were often excluded from participating in studies conducted with robots between 2016-2022 This paper addresses this need for a neurodivergent scale for interacting with robots. Additionally, the inclusion of neurodivergent speech patterns considerations for large language models and design for social robots. Research suggests the current representations of social robots to be deficient in autistic representation (Rizvi et al., 2024). Further, HRI research notes the centrality of a medical model in place of a society model of autism with social robots. New fields in applied critical disability studies and crip technoscience focus on ensuring access, interdependence and disability justice to their work (Rizvi et al., 2024). In particular, social-emotional-sensory designs are used to map more effective affective computing interfaces. While power imbalances continue to ensue and robots are relegated mentorship roles a focus on de-emphasizing stereotypical social norms acknowledges the necessity of designing for autistic users. Stereotypical cognitive-affective models currently used in the design of social robots may follow heteronormative (Topić, 2023) social behaviors and rules. Implied stereotypical ableism accounts can consequentially be noted when viewed through the lens of heteronormative large language models and in the neurotypical design of social robots.

Keywords: Neuroqueer pedagogy, social robots, language learning,

1. Introduction

Recent calls from UNESCO regarding concerns for stereotypical identities (Dennler et al., 2025) match recent studies quests for diverse speech datasets (He et al., 2024). Large Language Models (LLMs) are used to encourage adaptability between robot and users. A review of human-robot interaction (HRI) studies (Rizvi et al., 2024) found that autistic individuals, were often excluded from participating in studies conducted with robots between 2016-2022. “Our work uncovered that about 90% of HRI research during the timeline explored (2016-2022) excluded the perspectives of autistic people, particularly those from understudied groups” (Rizvi et al., 2024, p. 1). Further, Human Robot Interaction (HRI) research is noted as centered around medical models, while emerging best practices suggest affirmative based and societal models. When autism is viewed from a deficit-model autism is seen as something to be fixed (Rizvi et al., 2024). Applied critical disability studies and crip technoscience are two new fields of research with a focus on ensuring access, interdependence and disability justice to their work (Rizvi et al., 2024).

In particular, autistic models and diversity models may consider social-emotional-sensory designs to map “more effective affective computing interfaces” (Zolyomi & Snyder, 2021 as cited

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in Rizvi et al., 2024). Rizvi et al. (2024) notes power imbalances may exist for autistic and diversity designs and autistic end-users when robots are relegated mentorship roles. Concerns may also be raised for ableism approaches to design principles and a lack of validity constructs for a neurodivergent scale for interacting with robots. Perhaps of even greater interest is a scale for determining placement on the autism spectrum scale. Currently, ableism holds the perspective that autistic users are deficient in human attributes. Further concerns consider the potential to be viewed as “harassing” a robot that has been designed with stereotypical social norms for communication (Rizvi et al., 2024). Cano et al. (2021) refers to ableism when acknowledging autistic users may be viewed as emotionally deficient when observing the design of social robots. Cano et al. (2021) notes social robots are purposefully designed with stereotypical cognitive-affective models, and these models follow social behaviors and rules. Beyond the implied stereotype presented above, further ableism accounts can be noted when viewed through the lens of large language models that are currently being used to help design social robots (Cooper et al., 2024; He et al., 2024, Lin et al., 2024).

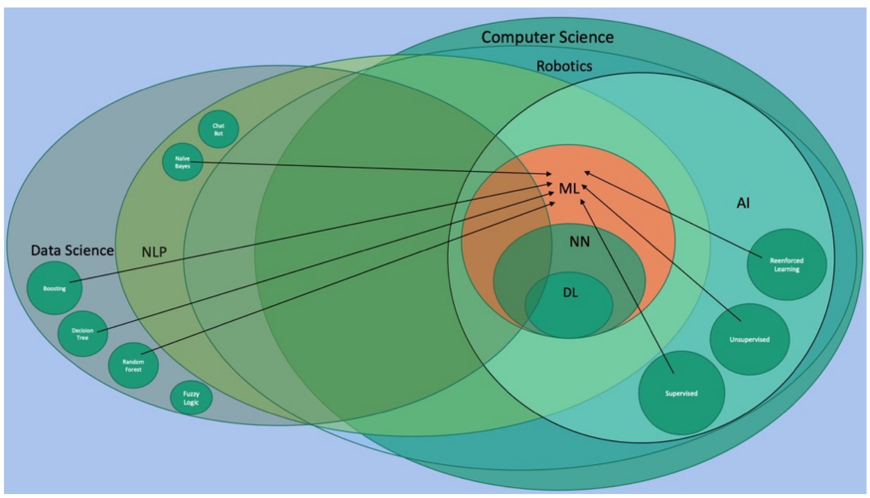

Figure 1 Categorization and Conceptualization of Artificial Intelligence (AI)

2. Historical Ontology

Artificial Intelligence (AI) can be defined in many ways, for the purposes of this paper AI is defined as the automation of activities we associate with human thinking, like decision making and learning. As such AI is a representation of knowledge with built in automated reasoning and machine learning to adapt to new information and natural language.

	Human	**Rational**
Thought	Systems that think like humans	Systems that think rationally
Behaviour	Systems that act like humans	Systems that act rationally

AI also has a history dating back to earlier conceptual models of intelligent agents such as ‘von Neuman’ (von Neumann, 1945) and a simplistic description of a processing unit, control unit, memory, external mass storage and input/output mechanisms. In 1956, the Dartmouth conference heard from McCarthy; Minsky, Simon, Newell, and Samuel as primarily the early conceptualists of AI. The evolution of AI considered the Age of Reasoning (logic-based, heuristic searches) in the 1960s, the Age of Representation (Rule-based, knowledge engineering, expert system) in the 1990s, the Age of Machine Learning (Big data-driven and autonomous learning) in 2015 and predicts the Age of Superintelligence in 2045. Knowledge-based systems or expert systems were acknowledged to have begun in 1969 a few years ahead of an industrial AI revolution before a scientific focus emerged in 1987 with the introduction of neat and scruffy labels to describe alternative types of AI.

While certain AI (medical diagnosis, design and speech recognition applications) are considered successes, emerging fields of scholarship in applied critical disability studies and crip technoscience question the success through an autistic and neurodivergent lens for language and design. The concept of autonomy and adaptivity in relation to autism and neurodivergent pedagogies has risen as a criticism of current social robots based on social norms and natural language.

3. Large Language Models (LLMs)

Processes such as natural language processing, neural networking, speech recognition and image recognition are part of artificial intelligence in robotics. Initially, AI was a rule-based expert system, now in 2026 considerations for breaking social norms and celebrating diversity through the creation of artificial neural networks (ANNs) for interpreting neurodivergent speech patterns (prosody, rhythm and spectral features) in natural language processing, neural networking, speech recognition and image recognition is presented in this paper as the future of social robotics.

Bowman (2024) notes there are eight things to know about LLMs:

1) LLMs predictably get more capable with increasing investment, even without targeted innovation (scaling measures to determine the amount of data they are fed, their size (measured in parameters), and the amount of computation used to train them (Ganguli et al., 2022)
2) important LLM behaviors emerge unpredictably as a byproduct of increasing in-vestment. (largely not possible to predict when models will start to show specific skills or become capable of specific tasks) (Ganguli et al., 2022)
3) LLMs often appear to learn and use representations of the outside world (representations allow them to reason at a level of abstraction that is not sensitive to the precise linguistic form of the text that they are reasoning about)
4) There are no reliable techniques for steering the behavior of LLMs (they can't guarantee that an AI model will behave appropriately in every plausible situation it will face in deployment.)
5) Experts are not yet able to interpret the inner workings of LLMs (what kinds of knowledge, reasoning, or goals a model is using when it produces some output?)
6) Human performance on a task isn't an upper bound on LLM performance. (potentially outperform humans on many tasks)
7) LLMs need not express the values of their creators nor the values encoded in web text. (When an LLM produces text, that text will generally resemble the text it was trained on)
8) Brief interactions with LLMs are often misleading (models can be sensitive to the contents of their instructions in idiosyncratic ways)

4. Systems That Act Like Which Type of Humans

Research suggests that systems are designed with four types of cognitive tasks: knowledge representation; automated reasoning; machine learning; and natural language processing to imitate the behaviour of humans. This acknowledgement understandably suggests and implies an ideal model has been selected for how to retrieve and answer questions with automated reasoning, how to adapt to new circumstances and how to communicate with a human. Algorithmic and computational thinking therefore, has stored information effectively and efficiently according to knowledge representations or an ideal not necessarily neurodivergent individual. This information also implies that mentorship with social robots encourages a deficit-based instead of affirmative response to neurodivergent decisions and processing. The additional concept of expert systems that enact "if-then" rules are not expected to select a neurodivergent response or solution to a problem (Rizvi et al., 2024). Artificial Neural Networks (ANN) models replaced if-then models, however, ANNs are also not the ideal response, due to the reported lack of autism-based studies (Rizvi et al., 2024) in designs for neural networks.

Machine learning conceptualizes autonomy and adaptivity by allowing a system to improve its performance as it gains experience and consequentially. more experiential data. Cognitive modelling and affective computing are also equally related to concerns from a lack of neurodivergent input into social robotics as the current systems are designed to respond to expressions of human feelings that may not be perceived or even observed by an autistic individual. The intelligent agent, in this example, acts upon the environment using observation through sensors of a heteronormative designer. Bowman (2024) notes, "As LLMs become more capable of using human language and human concepts, they also become more capable of learning the generalizations we would like" (Ganguli et al., 2023 as cited in Bowman, 2024).

5. Knowledge Representation & Reasoning

Without neurodivergent designers and representations in social robotics, it is virtually implausible that a social robot will act in a way that matches the description of the environment and the drawn inferences from that representation as its autistic user. Most certainly of interest is the way in which the robot and user differ in how they generate new pieces of knowledge and how to deal with uncertain knowledge (Russel & Norvig, 2021). Additionally, the construction of a sequence of actions to achieve identified goals or adaptations to the executed plan if the environmental context changes would demand a level of flexibility not expected with autistic users. Russel and Norvig, (2021) acknowledge the following key components for intelligent systems: acceptable sensory input for vision and sound, interactions with humans to understand language and recognize speech, generate text and the ability to modify the environment. Perhaps what is needed in the scaffolding is a vocabulary and reasoning process that matches the autistic user and a set of problem-solving cues to help the robot-user pair reason together about how to problem solve when the robot-user pair initial attempts do not work. Ideally, the robot working memory can also help with the user executive function to remind of path dependencies and past errors.

6. General vs Narrow AI

In this specificity of autistic users and a robot with the expert system of only one user, the concept of Narrow AI considers how AI handles one task (weak AI), such as solving a problem unknown to it and one it has no memory or experience with towards the development of General AI as it begins to handle a plethora of new problems based on gained experience with its one user (strong AI). Strong AI use rule-based expert systems, model-based and case-based reasoning focused on information specific to each problem area and without generalizability. This is acknowledged by the concept of strong methods which emphasize the vast amount of knowledge, specificity and management of uncertainty required for autistic users to feel capable of adapting to new situations and change.

7. Atypical Speech Patterns

There are noted atypical speech patterns in autism and these are distinguished by analyzing prosody (Li et al., 2018; Ma et al., 2024), rhythm and spectral features (Hu et al., 2024). Li et al. (2018) acknowledges prosody is found in paralinguistics and relates to several communicative functions such as intonation, tone, pitch, stress, and rhythm. Other features of prosody consider emphasis, contrast and the affective state of the speaker (Li et al., 2018). In Li et al., (2018) study they modeled the atypical prosody abnormality using both the traditional strategy and the deep learning framework. Hu et al. (2024) note prosody features are directly related to emotional and syntactical aspects of speech and that these are often atypical in autism spectrum disorder (ASD). Hu et al. (2024) goes on to suggest spectral features are reflected in the quality of the sound and harmony. Due to the sophistication of spectral features subtleties in speech are not readily apparent "through simple auditory observation" (p. 4).

8. Diversity Aware AI

The anticipated value of diversity aware AI can be found in Recchiuto et al. (2022) description, "awareness will introduce a crucial innovation in social robotics. It will produce robots that can re-configure their behavior to recognize and value the uniqueness of the person they interact with to promote respect for diversity, inclusion, and equal opportunities". Diversity aware AI machines strive to "give people equal opportunities by preventing sensitive attributes (e.g. ethnicity, sex, religion, age, pregnancy, familial, or disability status) to be used for discrimination" (Recchiuto et al., 2022). Preliminary designs of Large Language Model-Based social robots for autistic students have begun to emerge (He et al., 2024; Kang et al., 2024; Lee et al., 2026) some researchers have been left disappointed (Kappas et al., 2023). The need for a neurodivergent scale for interacting with social robots (Abbo et al., 2025) is urgent.

9. Conclusion

There is a need for diverse and inclusive speech datasets (Abbo et al., 2025; Ganguli et al., 2022; 2023). This paper addressed this need through the perspective of autism and neurodivergent speech patterns and the review of current diversity aware AI models. Recent calls from UNESCO regarding concerns for stereotypical identities (Dennler et al., 2025) match recent studies quests for diverse speech datasets (He et al., 2024) and diversity aware AI models (Oleynik et al., 2025; Recchiuto et al., 2022; Reutlinger et al., 2025). A review of human-robot interaction (HRI) studies found that autistic individuals, were often excluded from participating in studies from 2016-2022 (Rizvi et al., 2024) and this paper calls for a neurodivergent scale for interacting with social robots (Abbo et al., 2025).

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Appendices

Appendix A – Proposed Questionnaire Neurodivergent Scale for Interaction with Robots

Scale Items

1. The robot is more like me than anyone else I know
2. Sometimes I stare at the robot
3. I think I can share my thinking with the robot without speaking
4. The robot and I will be together forever
5. My robot can tell what I am feeling, when I am sad, it can tell I am sad
6. I game my robot a name
7. I feel comfortable undressing in front of my robot
8. I believe that my robot is the same with me as it is with anyone