Disparities in Autism Spectrum Disorder Diagnosis:

Examining Individual and Socioeconomic Predictors of Diagnostic Age and Provider Type

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Abstract

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Autism spectrum disorder (ASD) can be reliably diagnosed as early as 18-months-old, however, the average age of diagnosis is 48 months or later. It is critical that individuals suspected of having ASD are evaluated as early as possible, as early intervention has been shown to have the most robust long-term outcomes. Individual and systemic barriers prevent underserved populations from receiving a timely diagnosis of ASD. While these disparities have been outlined in the literature, to date, a large-scale study has not examined the impact of these individual predictors, along with access to resources, has on the timeliness of diagnosis. As such, the present uses linear modeling with data from the SPARK study to examine how individual and socioeconomic predictors impact the timing of diagnosis, particularly for participants from

traditionally underserved groups. Additionally, the present study will examine the role of school psychologists in the identification of ASD based on individual and socioeconomic factors. To achieve this, logistic regression was used to model the probability of school-based ASD diagnosis. Results indicate that cognitive impairment, symptom severity, diagnosis year, and BIPOC status were predictive of diagnosis age. Additionally, interactions with cognitive impairment and symptom severity were significant. For school-based diagnoses, BIPOC individuals were more likely to be diagnosed, while females were less likely. Age band and diagnosis year also interacted with the likelihood of receiving a school-based diagnosis. These findings highlight the importance of addressing both individual and socioeconomic factors that contribute to diagnostic age for ASD, particularly for underserved populations. The results suggest that greater attention is needed to ensure equitable access to timely evaluations and interventions, especially for BIPOC individuals and females, who are at risk for later diagnoses despite early indicators of ASD. Additionally, the role of school-based identification is crucial, as individuals from undeserved communities are more likely to receive diagnoses in the school setting.

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This dissertation is dedicated to my wonderful parents, my phenomenal husband, beautiful daughter Camellia Lily, and my dogs.

CHAPTER ONE: INTRODUCTION

Overview

Autism spectrum disorder (ASD) is characterized by deficits in social communication, as well as the presence of restricted interests and repetitive behaviors (American Psychiatric Association [APA], 2022). Individuals with ASD can be reliably diagnosed as young as 18-months-old (Baird et al., 2000; Zwaigenbaum, et al., 2016). However, the median age of diagnosis in the United States is four years old (Maenner et al., 2023). The advanced age of diagnosis remains stagnant despite the increasing prevalence of ASD and vast body of research centered on early identification and diagnosis. It is critical that the average age of diagnosis is decreased, as research has found that earlier diagnosis provides access to early intervention (Koegel, Koegel, Ashbaugh & Bradshaw, 2013), which in turn, has the most robust long-term outcomes.

Over the last several decades the prevalence of ASD has drastically increased, with current rates being estimated as 1 in 36 individuals (Maenner et al., 2023). It is likely that the increase in ASD prevalence is due to a heightened awareness of the etiology and development of ASD, as well as improvements in defining the presentation and diagnosis (King & Bearman, 2009). However, researchers have also theorized that the rise in ASD prevalence cannot solely be explained by increased awareness and changes in diagnostic criteria (Prior, 2003). Therefore, the increased prevalence can be explained, simply, by the increased frequency of individuals that develop ASD.

With the rise in prevalence, the field has moved toward developing a standardized approach to ASD diagnostic evaluations. Symptoms of ASD can be observed in infancy and be differentiated as early as 12- to 18-months (Stone et al., 1999; Landa & Garret-Mayer, 2006).

Notable developmental differences in individuals with ASD occur within social (Lord, 1993) and language (Filipek et al., 1999; Landa, 2007) development in infancy. These challenges, unless intervened upon early, persist into adulthood and may require extensive support and ongoing care. Previous studies have shown that early intervention is critical for long-term outcomes. Interestingly, some children with ASD that receive early intervention have such robust changes that, at the age of 8, they no longer meet criteria for an ASD diagnosis (Rogers et al., 2000).

There are several predictors associated with age of diagnosis, including socioeconomic status, cognitive ability, race, assigned sex, and severity of the symptoms. Accessibility within the community to diagnostic resources also impacts age of diagnosis. Specifically, individuals from lower socioeconomic status, people of color, females, individuals with higher cognitive ability and more subtle symptoms are at an increased risk of a later diagnosis (Hiller et al., 2014; Rosenberg et al., 2011). Access to resources also impacts timeliness of diagnosis, as families in low-resource areas are required to travel to access the support they need to obtain a diagnosis (Ning et al., 2019). Accordingly, efforts to decrease the gaps in access to ASD diagnosis and treatment are critical and should focus on identifying individuals most at risk of a delayed diagnosis.

Study Aims

The present study aims to identify the relationship between the diagnostic barriers and ASD diagnosis in a large-scale study. The present study will use parent- and caregiver-reported data from the Simons Powering Autism Research for Knowledge (SPARK; Feliciano et al., 2018) to examine how access to resources (e.g., area deprivation index) impact diagnosis age, including a family history of autism, cognitive ability, race, diagnosis year, assigned sex and symptom severity impact the diagnostic age in children and adolescents with ASD across the

United States. This will be completed using linear regression, with diagnostic age being the outcome variable, and diagnosis year, family history of ASD, area deprivation income, cognitive ability, race, assigned sex and symptom severity as predictors. Additionally, intersectionality between group membership will be analyzed using interaction variables. The second research question will address the role of the psychologist in school settings in ASD identification. Specifically, what is the likelihood that a child from a traditionally underserved community will first be identified with autism by a school-based team? This will be achieved through logistic regression, with diagnostic provider as the outcome and area deprivation index, diagnosis year, family history of autism, age, cognitive ability, race, assigned sex and symptom severity as predictor variables, along with their interactions.

Results of the present study have practical implications for the field of school psychology. Specifically, all children in the United States have the right to a Free and Appropriate Public Education (FAPE; IDEA 2004), including children with disabilities through special education services. Schools have the federal obligation to conduct child find (IDEA, 2004) to help identify children with disabilities in need of special education services. This includes children who reside in low-resource areas, as they do have free access to public schools. As such, school psychologists should assist in the screening and identification of ASD in their communities, particularly in districts located in areas with little- to no- diagnostic resources.

CHAPTER 2: LITERATURE REVIEW

Autism Spectrum Disorder (ASD) was first introduced in the medical field in 1943 by Dr. Leo Kanner. In his seminal paper, he described 11 cases in which children had remarkably similar presentations that, in turn, formed a unique syndrome not previously described in the literature. Specifically, he noted challenges with social-reciprocity, inability to relate to others (with intact ability to relate to objects), delayed communication development, excellent memory, sensory sensitivities or sensory seeking behaviors, insistence on sameness, and repetitive behaviors. This study led to the newly formed medical diagnosis of early infantile autism, which led to an increase in the interest and subsequent research in autism. Simultaneously, Dr. Hans Asperger (1944) reviewed cases of children with a similar presentation as the children in Dr. Kanner's study. However, children in Dr. Asperger's study had significantly higher communication and cognitive abilities which led to the creation of the diagnosis of Asperger's syndrome. From there, the prevalence of autism increased, as well as the understanding of the disorder.

Diagnosing Autism Over the Years

For years, ASD was speculated to be childhood schizophrenia. However, in 1980, autism was added as a diagnosis to the DSM-III as a pervasive developmental disorder (APA, 1980). From there, it was revised to include pervasive developmental disorder not otherwise specified (PDD-NOS) in the DSM-III-R (APA, 1987). Autism was then updated to be a spectrum in the DSM-IV-TR (APA, 1994) to reflect the heterogeneity of the disorder. The autism spectrum included Asperger's disorder, PDD-NOS, autism, childhood disintegrative disorder and Rett syndrome. That is, the separate disorders were created to specify level of functioning based on the disorder, and the degree to which the patient was impacted; as well as describe specific syndromes. This changed in the DSM-5 (APA, 2013), where these disorders were collapsed into

a singular diagnosis of autism spectrum disorder, thereby eliminating differential diagnosis between autism, PDD-NOS, Asperger's disorder, and Childhood Disintegrative Disorder. This change was controversial within the ASD community; however, it was implemented because of the lack of reliability in the criteria that diagnosticians used for differential diagnosis between Autism, PDD-NOS and Asperger's disorder (Lord et al., 2012). As such, diagnosticians are no longer required to complete differential diagnosis between the spectrum disorders as a method to represent level of severity and functioning. Severity and cognitive ability are now reflected in specifiers for the diagnosis.

Present Diagnostic Criteria

Presently, the DSM-5-TR (APA, 2022) requires specific criteria are met within two domains for an ASD diagnosis. First, the individual must show pervasive impairments in social communication, as well as being functionally impacted by the presence of restricted interests, repetitive behaviors and sensory behaviors or interests. The symptoms must be present in early development, must impact functional ability and cannot be otherwise explained by intellectual disability or a general developmental delay. While intellectual disability is no longer a rule-out for ASD, it is important that the diagnostician consider developmental level when conceptualizing social-communication abilities. Cognitive and language impairments are now specified through coding. Severity for both domains is also specified through coding in three levels. An individual with a severity level of one indicates that they require some support, level two indicates the individual requires substantial support and level three indicates an individual requires very substantial support.

Within the social-communication domain, the individual must demonstrate persistent deficits in each of the outlined criteria. The three criteria consist of social-emotional reciprocity

(e.g., challenges within conversations, effectively communicating thoughts and feelings, etc.), nonverbal-communication (e.g., lack of gestures, fleeting or inconsistent eye contact, limited facial expressions) and deficits in developing and maintaining relationships (e.g., limited insight into relationships, difficulty with initiating and maintain friendships, difficulty relating to same-aged peers, etc.). Individuals must also demonstrate deficits or challenges in at least two of four areas within the restricted interests and repetitive behaviors domain. This includes stereotyped or repetitive motor movements, use of objects, or speech; insistence on sameness; inflexible adherence to routines or ritualized patterns of verbal or nonverbal behaviors; highly restricted and/or fixated interests that are abnormal in intensity and focus; and hyper- or hypo-reactivity to sensory input or unusual interest in sensory aspects of the environment.

Current Diagnostic Process

Currently, the average age of ASD diagnosis is 48 months (Maenner et al., 2023). This is in stark contrast with the literature that has demonstrated that ASD can be reliably diagnosed as early as 18-months (Zwaigenbaum, et al., 2016). It is critical that an individual with ASD obtains a diagnosis as early as possible, as an official diagnosis is the gateway to early treatment. Robust long-term outcomes are associated with early treatment, with some children demonstrating such strong social-communicative gains, that they no longer meet criteria for ASD (Rogers et al., 2000). As such, the field has progressed toward creating practices and policies that promote the importance of early, evidence-based treatment to increase social-communicative skills and decrease engagement in restricted and repetitive behaviors that impact the individual's ability to function independently. Taken together, an accompanying shift in the diagnostic field that promotes and improves early identification practices is vital. Practices should be designed to be accessible to all populations.

The current gold-standard diagnostic model for ASD is extensive. Children that are suspected of having ASD are often referred for an evaluation that consists of a diagnostic interview of the child's developmental history and the Autism Diagnostic Observation Schedule, 2nd Edition (ADOS-2; Lord et al., 2012). After a diagnostician gathers relevant information for the evaluation, they consult the DSM-5-TR (APA, 2022) regarding diagnostic criteria and differential diagnosis. Then, they make the diagnostic decision regarding ASD and provide feedback to the family. Though this process provides robust information regarding the child's current presentation, it is costly and requires a significant amount of time to complete (Stone et al., 2000). Therefore, there is a need for streamlined diagnostic services for ASD that can reduce wait-times and the cost associated with obtaining an evaluation.

Novel Approaches to Diagnosing ASD

Gerdts et al., (2018) demonstrated that an interdisciplinary team evaluation approach can shorten the diagnostic process, including reduction in wait-times and costs compared to single-discipline evaluations. Individuals suspected of ASD, including those using Medicaid, were referred to a local ASD clinic. After intake, they were triaged into one of three categories based on initial impressions of the child's presentation. Children were triaged to an evaluation conducted by a physician, a single-discipline psychologist, or the interdisciplinary team. Interdisciplinary team evaluations were streamlined to occur within one session for 90% of patients, thereby reducing waitlists at the local ASD center. Billable rates were also significantly reduced for the interdisciplinary team evaluations compared to the single-discipline visits. These visits were also associated with high parental and caregiver satisfaction with the diagnostic process, as well as increased engagement in follow-up care. Taken together, this model is an

efficient diagnostic approach that provides a comprehensive evaluation, reduced wait time to diagnosis, and, immediate access to follow-up care (Gerdts et al., 2018).

Multi-step, universal screening models to increase early detection of ASD are also commonly used within the general population. Chakrabarti et al., (2005) proposed a 4-step model in which children are first screened by pediatricians for neurodevelopmental disorders. If a child is identified as having a developmental delay, they are referred to be observed by a Child Development Team (CDT). From there, children are evaluated by a multidisciplinary team, and, when applicable, evaluated specifically for ASD. A strength of this model is that screening begins as early as 6- to 8-weeks of age and development is monitored throughout childhood. However, the model has multiple steps that make the process complicated and extends the time to diagnosis.

Oosterling et al., (2010) collapsed the previous model into a two-step process specifically aimed at identifying individuals that are at high risk for ASD, as opposed to neurodevelopmental disorders in general. In this model, children are screened at 18-months within pediatric and community settings using the Early Screening of Autism Traits (ESAT) Questionnaire. Children identified as being at high-risk for ASD are then referred to a multidisciplinary diagnostic team, where they are further evaluated for ASD. This model was remarkably advantageous for streamlining the diagnostic process, as children that were identified through the early detection program received their diagnoses 21-months earlier than those that received a diagnosis through the typical evaluation process. This indicates that universal screening is beneficial for identifying and then diagnosing individuals at-risk for ASD, especially at an early age.

In addition to the ESAT, which requires significant training and expertise in ASD, several other screeners have been implemented to streamline early identification and diagnosis

and avoid the financial burden associated with a comprehensive evaluation. For example, Charman et al., (2001) developed the Modified Checklist for Autism in Toddlers (M-CHAT) to identify toddlers with elevated symptoms of ASD. The M-CHAT is a free tool that can be downloaded online and is often used by medical providers when parents and caregivers have concerns about their child's development that are consistent with ASD. Stone et al., (2000) developed the Screening Tool for Autism in Toddlers (STAT), which is a short, interactive and semi-structured session that measures play, directing attention, motor imitation and requesting (i.e., symptoms associated with ASD). The STAT can be reliably used with infants as young as 14-months and has strong psychometric properties, including high levels of reliability and concurrent validity with the ADOS-2.

Finally, Choueri et al., (2021) administered the Rapid Interactive Screening Test for Autism in Toddlers (RITA-T) to participants from traditionally underserved populations (e.g., low income or culturally diverse groups) that were enrolled in an early intervention program. Similar to the STAT, the RITA-T has interactive activities that measure joint attention, social awareness and human agency; and has strong psychometric properties, such as strong reliability and concurrent validity with the ADOS-2. Use of the RITA-T significantly reduced wait times in the diagnostic process, with the average diagnostic decision being made within six weeks. These findings are noteworthy, as the use of the RITA-T simplified the diagnostic process, specifically in individuals that come from low-income and culturally diverse households.

Biological Markers Used to Detect ASD

Diagnostic criteria for ASD are highly subjective, resulting in high levels of variability in diagnostic practices (Lord et al., 2012). As such, some researchers have moved toward identifying biological markers that can reliably diagnose ASD at an early age. The most

frequently studied biomarker associated with ASD is genetics. There is strong evidence that ASD has an underlying genetic predisposition. For example, monozygotic twins have higher concordance rates of ASD (i.e., both twins have ASD) compared to dizygotic twins and siblings (Rosenberg et al., 2009). Interestingly, 39% of genetic mutations associated with ASD are classified as *de novo* mutations, or mutations that are not inherited (O'Roak et al., 2014). There are no single mutations that can completely account for ASD, and as such, an emerging alternative to current identification practices include the use of a *Genotype-First* approach (Stessman et al., 2014). In this model, individuals at risk-for neurodevelopmental disorders are identified through targeted exome sequencing, in which a specific genetic mutation identified. From there, diagnosticians provide a comprehensive evaluation to identify common phenotypic presentations associated with inherited and *de novo* mutations (e.g., spontaneous genetic mutations not present in either biological parent), including assessing for ASD. Thereby reversing the current diagnostic model by using a bottom-up approach to identify genetic markers associated with ASD.

The use of eye-tracking paradigms has also become more common in early ASD identification research. Klin et al., (2009) found that infants with ASD demonstrate a distinct pattern of gaze in an eye-tracking paradigm, where they had longer duration of eye-gaze for non-biological motions (i.e., motion not from a human) than biological motions (i.e., a human clapping, walking, etc). Similarly, Jones et al., (2008) demonstrated that distinct patterns of eye-gaze (e.g., gaze at another individual's face) can help differentiate between ASD, typical development, and children with developmental delay in toddlerhood. Toddlers with ASD spent less time looking at faces compared to their same-aged and developmental-level peers. Taken together, eye-gaze patterns are an example of a robust early developmental predictor of ASD, as

well as for differential diagnosis. However, these paradigms are expensive and costly to maintain (Vargas-Cuentas et al., 2017). As such, eye-tracking paradigms are not considered to be a standard part of current early identification practices in the general population.

In addition to eye-tracking and genetics, brain activity, as measured by Electroencephalography (EEG), is also strong biomarker that can predict ASD (Gabard-Durnam et al., 2019). Frequencies and amplitudes measured by EEG in individuals with ASD are substantially different from neurotypical individuals. As such, EEG can be used to differentiate ASD and typical development in early infancy, particularly within the first year of life. Nicotera et al., (2019) also demonstrated that EEG abnormalities can be used as a biomarker for severity of ASD symptoms, as individuals with more severe ASD symptoms (i.e., as measured by requiring more support and having lower cognitive ability) have more abnormalities in amplitude across alpha and delta waves compared to those with milder symptoms. Taken together, EEG can provide neurophysiological data that can be used to detect ASD. However, similar to eye-tracking, it is time-consuming and expensive to maintain. As such, it is also not a standard process of early identification practices.

Standardizing Autism Spectrum Disorder Diagnosis

In addition to an increased understanding of the nature of ASD, there has been a movement toward standardizing ASD diagnostic evaluations. ASD is considered to be a highly heterogeneous disorder, meaning that there is significant variability in the presentation of symptoms across individuals (Masi, et al., 2017). This makes evaluations effortful and require diagnosticians to have specialized training in the diagnosis and assessment of ASD to determine if the presenting concerns are consistent with a diagnosis of ASD. Thus, the field has moved toward using the gold-standard diagnostic model to disentangle external factors that may impact

the overall heterogeneity of ASD. Due to the pervasive nature of ASD, it is recommended for practitioners to receive parent and teacher input on behavior, as well as conduct cognitive, adaptive, and social-emotional assessments to provide differential diagnosis. After the data has been collected, a diagnostician should conceptualize the information and use the DSM-5-TR (APA, 2022) to determine if the individual meets criteria for ASD, as well as determine the severity level and any other co-occurring conditions.

A challenge with the current gold-standard diagnostic model is that assessments, such as the ADI-R and the ADOS-2, require extensive training and consistent reliability checks to ensure that the diagnostician has not demonstrated examiner drift (e.g., decreased reliability in coding over time). The gold-standard approach is particularly useful in research settings. However, it is not practical in community-based settings, as it is time consuming and costly to conduct. Diagnosticians must be formally trained in and achieve clinical or research reliability to administer either of these assessments. This makes investing in this training impractical for many diagnosticians because it is not easily accessible.

School-Based Identification

ASD identification also occurs within the school setting, as a part of the special education evaluation system. The Individuals with Disabilities Improvement Act (IDEA, 2004) includes "Child Find," which aims to identify children with disabilities that are in need of intervention and specially-designed instruction. These services provide individuals with disabilities with a Free and Appropriate Public Education (FAPE; IDEA, 2004). As a part of IDEA, there are several programs in which a child can become eligible for special education services in their local school district. IDEA, Part B (2004) makes provisions for special education services under federal law, where individuals with disabilities have the fundamental right to access FAPE.

When educators within the school district collect data that shows that the student is not appropriately accessing their education, a special education evaluation is completed. If the student qualifies for services, they receive specially designed instruction in all areas of education that are adversely impacted by their disability. This not only includes specially designed instruction in academic areas such as reading, writing, and math, but social skills, adaptive skills, communication, motor skills, and behavior.

Part C of IDEA (2004) implements early intervention services to decrease the impact that having a disability has on long-term outcomes. A primary aim of Part C (IDEA, 2004) is to provide evaluations to parents and caregivers that have concerns about their child's development. Children that qualify are provided early intervention services to improve their development. Part C of IDEA (2004) is beneficial for families from low-income households, as evaluations and treatment are provided through the local school district and are free to the public for children ages 0-5. Part C of IDEA (2004) bridges some of the gaps in disparities that occur within the healthcare system at an early age. Though implementation of Part C of IDEA (2004) has increased school-based identification of disabilities and access to services, there are no clear initiatives to increase ASD identification specifically within the school setting.

Current Models of School-Based Identification

Despite the increasing number of students that are identified as having ASD through their school district (Yeargin-Allsopp, et al., 2003), there are few studies that have examined the systematic effects of a school-based diagnostic model of ASD. Noland and Gabriel (2004) outlined a model for a school-based ASD identification program. They indicate training should occur at the district, school, and classroom levels. At the district and school level, educators should receive general training in the etiology and presentation ASD and its treatment. They also

outline that special education providers should implement a universal screener to identify students that are at-risk for developing ASD. From there, students who are suspected of having ASD, or, that are identified as having elevated symptoms from the screener, can be referred to the ASD evaluation team for further evaluation. In said evaluations, the school-based team determines whether a student meets eligibility criteria for the *educational category* of Autism. If the student does meet criteria, it is then the team's responsibility to provide intervention and specially designed instruction in the identified areas of need and assist in the development of the Individualized Education Program (IEP).

What is the Role of the Psychologist within a School Setting?

School psychologists are in an excellent position to evaluate for ASD. School psychologists are expertly trained in a variety of assessments and have knowledge of child development, particularly through a lens of developmental psychopathology. In some school districts, school psychologists are trained to use the gold-standard approach to evaluating ASD (Akshoomoff et al., 2006). However, this is not a common practice and specialization in ASD is typically rare. School psychologists can also provide consultation to other educators about treatment and evidence-based practices that can be used with individuals with ASD, particularly as it relates to the individual needs and challenges that are outlined in evaluations (Williams et al., 2005).

Medical Diagnosis vs. Educational Category

It is important to note that there are significant differences in the *educational categ*ory of Autism and having the *medical diagnosis* of ASD. Although both educational and medical evaluations for ASD are part of the broader process of identifying disabilities (e.g., to receive

treatment or services), they are conducted within different sectors and their impact is confined to those distinct areas. A *medical diagnosis* of ASD does not necessarily qualify a student for special education services under the category of Autism. The student may have a neurodevelopmental disorder, however, in order to receive special education services, the disability must have an adverse educational impact that requires specially designed instruction. In contrast, a student can qualify for services under the category of Autism without a medical diagnosis (i.e., in states that do not require a medical diagnosis). The educational category of Autism does *not* mean that the student has ASD, but, that they qualify for services in special education because they have deficits in social-communication skills and restricted behaviors that prevent them from accessing their education *and* require specially designed instruction. Therefore, if a school district's special education team qualifies a student for services, they are purely providing educational qualification in the category of Autism and not a diagnosis of ASD that can be utilized outside the school setting.

Medical Diagnosis

A *medical diagnosis* of ASD is given by a physician or licensed psychologist and can be used to access private therapeutic services and have the costs covered by insurance, such as Applied Behavior Analysis (ABA). To obtain a *medical diagnosis*, the individual needs to be evaluated by a licensed practitioner and must meet criteria as outlined in the DSM-5-TR (APA, 2022). In order to meet criteria for ASD, an individual must demonstrate impairments in social communication, as well as engagement in restricted and repetitive behaviors that impact daily functioning (APA, 2022). These impairments must be demonstrated in early childhood and must be present across multiple contexts (e.g., in the home, at school, within the greater community, etc.). The presenting concerns must not be better explained by other developmental disorders;

meaning, presenting concerns must be considered within the context of the individual's developmental level. The diagnostician must also consider the individual's presentation within the context of their culture, as expectations for social interactions and communication are highly dependent on the individual's cultural experiences. Diagnosticians must also specify the severity level of ASD, as well as accompanying intellectual or language impairment. Given that there has been substantial evidence of underlying genetic conditions associated with the development of ASD (O'Roak et al., 2012), diagnosticians are also advised to specify if the individual has an associated genetic condition as a part of their diagnosis.

Educational Category

While there are some similarities in what is required to receive an *educational category* qualification for Autism and that of a *medical diagnosis* of ASD, there are also substantial differences. To receive any special education services, a student must have a documented disability that adversely impacts their education which requires specially designed instruction. These criteria were mandated as a part of IDEA (2004) to allow students with disabilities to have FAPE. Per IDEA (2004), there are 13 eligibility categories for special education services, including "Autism." Eligibility is determined by a multidisciplinary evaluation team that include a school psychologist (e.g., a certified practitioner with at least a master's degree in educational psychology), a special education teacher, general education teachers, parents and caregivers, as well as related service providers (e.g., speech language pathologists, occupational or physical therapists, etc) as needed.

The Autism *educational category*, at the federal level, requires that an individual demonstrates deficits in their social skills, communication skills, and restricted interests or repetitive behaviors (IDEA, 2004). This closely aligns with the criteria outlined in the DSM-5-

TR (APA, 2022). However, considerations of impact are different for the *educational category*. In the DSM-5-TR (APA, 2022), the individual must demonstrate a particular number of deficits in each core area that impairs daily functioning. However, the *educational category* of Autism requires that an individual not only demonstrates impairments in the core domains and behaviors, but that said impairments must adversely impact their education. IDEA (2004) has created guidelines for eligibility criterion for the Autism category. However, each state has its own specific set of eligibility requirements, which has been shown to vary significantly.

MacFarlane and Kanaya (2009) found a significant degree of inter-state variability in the eligibility requirements used for the Autism *educational category*. This variability confounds the prevalence rates of the Autism category in the special education setting and thereby confounds broader educational needs specifically related to ASD. Some states require that evaluators use DSM-5-TR (APA, 2022) criteria as a part of their eligibility determination for the Autism *educational category*. Some states also require that a pediatrician or licensed psychologist must be a part of the evaluation for ASD, or the student must have a *medical diagnosis* to receive special educational services under the *educational category* of Autism. However, it is important to note that a *medical diagnosis* of ASD is *not* required as an eligibility criterion listed under IDEA (2004).

Implications of Educational Category

The additional eligibility criteria implemented by states has major implications for families who do not have the resources to obtain a medical diagnosis independently. That is, students with suspected ASD, but do not have a formal *medical diagnosis,* will likely be erroneously classified under a different educational category, and consequently, may not have the most accurate programming. Inaccurate rates affect state-level funding and decrease the

likelihood of allocated funding for ASD identification initiatives. It is likely that the states that require a pediatrician or licensed psychologist, or *medical diagnosis,* to be eligible for services under the *educational category* of Autism do so because there is a lack of practitioners within the school system that can reliably and expertly evaluate ASD. Accordingly, there is a need to increase the number and type of professionals (e.g., not solely school psychologists, for example, speech and language pathologists) that can provide comprehensive evaluations for students suspected of having ASD as a part of the special education multidisciplinary team. This would decrease the barriers that families have to the diagnostic process within the greater community.

Barriers to the Medical Diagnosis of ASD

The age at which parents first notice concerning symptoms, on average, happens around 18- to 24-months (Chawarska et al., 2007). Yet, the average age of diagnosis is 48 months (Maenner et al., 2023). ASD can be diagnosed reliably at 18 months (Baird et al., 2000; Zwaigenbaum, et al., 2016). Some studies have indicated that psychologists and physicians with expertise in ASD can differentiate between ASD and other neurodevelopmental disorders, such as intellectual disability, as early as 1-year-old (Oosterling et al., 2002). The delay between the time a child first presents with symptoms and the time a diagnosis is received has presented challenges to the field, as well as to families. A delayed diagnosis is harmful to children, as it is the gateway to receiving high-quality, evidence-based treatments that may be covered by the parent or caregiver's healthcare insurance. That is, insurance, both Medicaid and private, often require a diagnosis of ASD to cover treatment (Elder et al., 2016). Otherwise, the treatment is too costly for most families to access independently. Most families seeking a diagnosis experiences a lag between the time at which symptoms become noticeable, the first evaluation and a positive diagnostic outcome (Horovitz, Matson, Turgyin & Beighley, 2012). Goin-Kochel et al., (2006)

noted that this is partially due to a lack of clinical resources, such as limited diagnosticians in the community, as well as diagnosticians with training in ASD assessment.

The diagnostic delay that families experience is reflective of the systematic barriers that exist in the current diagnostic system. That is, there are challenges associated with obtaining a diagnosis for all families. These challenges are exacerbated by other systemic barriers in the healthcare system, such as disparities in the Black, Indigenous, People of Color populations (BIPOC), immigrant families, non-native English speakers, lower-income households and parents with lower educational attainment (Mandell, et al., 2005).

Systems-Level Barriers

At a systems level, barriers to receiving an early diagnosis include long wait lists, difficulty with finding licensed psychologists with the training and expertise to diagnose ASD, low confidence in ASD training in licensed psychologists with more generalized training, and seeing multiple medical providers or psychologists to obtain a clear diagnosis (Mansell & Morris, 2004; Carbone et al., 2016; Gerdts et al., 2018; Martinez et al., 2018; Kanne & Bishop, 2020). One of the mostly commonly reported reasons that individuals experience barriers in diagnosis is a lack of diagnosticians that have expertise in ASD within the community.

The demand for licensed psychologists and physicians that can diagnose ASD has placed a burden on the medical and health psychology field as there are not enough licensed diagnosticians with expertise in ASD that can serve the increased prevalence of ASD (Goin-Kochel et al., 2006). Therefore, the wait list for evaluations can be, on average, one- to two-years long (Kanne & Bishop, 2020). This is detrimental because it delays diagnosis, thereby preventing families from receiving treatment. Similarly, Soni et al., (2022) outlined several barriers that can delay the diagnostic process and described practical implications for diagnosticians. First,

individuals with ASD may experience common barriers to healthcare, including cost of treatment, shortages of diagnosticians and stigma around healthcare and diagnosis. Second, individuals with ASD experience system barriers in childhood, such as a lack of screening and diagnosis, or unclear referral pathways to diagnosis, etc. They conclude that stakeholders in the ASD community need to strengthen training on care of individuals with ASD, increase public awareness of ASD, promote identification diagnosis and treatment of ASD, and conduct research to understand the impact of ASD over the lifespan.

Elder et al., (2016) collected qualitative data regarding the most common barriers associated with receiving an early diagnosis of ASD. They interviewed stakeholders in the ASD community, such as parents, teachers, and healthcare service providers. They identified several emerging themes that act as barriers to diagnosis, including education, access, inaccurate screening practices, parental feelings of invalidation, and stigmatization of over the diagnosis. Specifically, stakeholders noted that that the community needs more professional and parent education of ASD. They also noted that access to professionals that can diagnose ASD, or having inadequate insurance coverage, was a significant challenge. Another important theme to note is that parents also struggled with feeling validated by their diagnosticians, as parents reported that the diagnosticians did not believe their concerns about their child's development and subsequently did not pursue a diagnosis any further.

In recent years, the COVID-19 pandemic compounded system level barriers to receiving diagnostic and treatment services, significantly impacting how families accessed care. Blumenthal et al. (2022) identified four crises within the healthcare system that emerged from the pandemic: a loss of insurance coverage (e.g., due to unemployment), financial losses for providers, exacerbated racial and ethnic inequities, and challenges in overall public health.

Additionally, the pandemic contributed to provider burnout (Jalili et al., 2021) and severely backlogged services. These disruptions had a profound impact on ASD healthcare as well. Diagnosticians had to continuously adapt their approaches as the pandemic evolved (Lang et al., 2021). At the onset of the pandemic, services were extremely limited due to stay-at-home orders, forcing diagnosticians to conduct evaluations through telehealth, even though ASD assessment measures lacked established reliability and validity for online platforms. When restrictions were lifted and in-person appointments resumed under strict parameters, providers shifted to a hybrid model. Later, as all restrictions were lifted, they had to adjust once again to fully in-person evaluations while maintaining precautions to prevent the spread of illness.

Furthermore, Spain et al. (2022) conducted interviews with diagnostic providers and found that waiting times increased for 58% of professionals during the pandemic. Families also experienced disruptions in services due to insurance denials of diagnostic evaluations and impressions conducted via telehealth (McNally et al., 2021). Insurance claims were denied because the delivery of covered and required diagnostic assessments, such as the ADOS-2, had not been validated for use through online platforms, rendering these assessments "invalid." This issue disproportionately affected individuals from racially diverse and socioeconomically disadvantaged communities. These barriers created significant challenges for families from underserved populations, despite telehealth assessments being shown to be valid, fiscally, and logistically advantageous for these communities. For example, Juarez et al. (2018) demonstrated the reliability and validity of telehealth delivery even prior to the onset of the pandemic and advocated for its use, particularly for disadvantaged families. However, insurance companies initially rejected these assessments, leaving families with limited access to traditional diagnostic routes and making timely diagnoses nearly impossible.

Individual-Level Barriers

Parikh et al., (2018) used latent class modeling of data from the Autism and Developmental Disabilities Monitoring Network (ADDM) to identify family- and individual-level factors associated with the age of ASD diagnosis in 8-year-old children. Family-level factors included poverty status, race, and parent education. Individual-level factors included a history of delayed language development and developmental regression. In their analyses, five distinct classes of individuals with homogenous socioeconomic and developmental trajectories emerged. The group with individuals who were predominantly white, had higher socioeconomic status, and had a reported language delay received a diagnosis at an earlier age compared to the classes that encompassed other racial categories, higher levels of poverty, and a history of developmental regression. This highlights the significant socioeconomic and racial disparities that exist in the current diagnostic model for ASD.

Interestingly, the age at which a parent first notices symptoms of ASD does not vary based on assigned sex, race, or socioeconomic status (Mandell, et al., 2005). Despite having significantly later diagnoses, individuals from underrepresented groups (e.g., females, BIPOC communities and low socioeconomic groups) present with a similar onset of symptoms and parents and caregivers first notice symptoms around the same time as white, male, or high socioeconomic groups. Therefore, delays in diagnostic age are not due to differences in detection of symptoms or parent education or awareness of ASD and child development.

Disparities by Assigned Sex

In addition to the system-level factors that act as barriers to receiving a timely ASD diagnosis, there are individual factors that can also impact the timing of a diagnosis. The assigned sex of the individual is a commonly reported factor associated with diagnostic barriers,

with females being diagnosed significantly later than males. Horovitz, et al., (2012) found that the average age of first concerns was significantly younger for females compared to males. In contrast, McDonell et al., (2021) found that age of first concern was not significantly different between females and males. Regardless, females with ASD are often diagnosed significantly later compared to their same-aged, male peers (Giarelli et al, 2010; Petrou, et al., 2018). The difference in diagnostic age is typically due to the differing presentation of ASD in females compared to males. Similar to the heterogeneity of presentation in individuals from other cultures, females also have more subtle symptoms and functional skills compared to males (Hiller et al., 2014; Young, et al., 2018). Thus, making the diagnostic process more complicated which delays time to diagnosis.

Delayed diagnosis in females can also be explained by a lack of instruments that were normed on females (Young et al., 2018). It is theorized that females often "mask" or "camouflage" their symptoms, meaning they have stronger social skills that can make their symptoms less detectable. In addition to stronger social skills, females also have less unusual play or restricted interests. Lockwood-Estrin et al., (2020) found several themes that can account for the diagnostic age difference in females. This includes misdiagnosis of symptoms as behavioral issues, confounding symptoms from other diagnoses, increased social-communicative abilities, and the ability to develop relationships and compensatory behaviors (e.g., masking and camouflaging). Similar to the overall need for expertly trained diagnosticians within the ASD field, there is also a need for diagnosticians to be trained specifically in the female ASD presentation.

Disparities by Race

Another commonly reported disparity within the ASD diagnostic process is race. Current literature has demonstrated that children from BIPOC populations are diagnosed later than White children, above and beyond other factors that influence access to services (Mandell, et al., 2002; Valienceti-McDermott et al., 2009). For example, Constantino et al., (2020) found that Black children in their sample were diagnosed at 64.9 months of age and approximately four years after parents first reported concerns. BIPOC children are also less likely than their white peers to have a documented ASD diagnosis, despite meeting criteria for the disorder (Mandell et al., 2009). This indicates a need in the field for a culturally-responsive evaluation model in which children that are BIPOC are prioritized.

BIPOC children also enter the diagnostic process at a significantly later age compared to white children, as well as having longer lengths of mental-health treatment prior to a diagnosis (Mandell et al., 2002; Wiggins, 2006; Jang et al., 2014). These findings illustrate that the substantial disparities in timing of diagnosis are not due to racial differences in parent awareness of ASD symptoms or different developmental trajectories. Instead, it is more likely that there is a systemic, racial barrier in the current medical system that prevents BIPOC families from gaining timely access to diagnostic services. BIPOC families that were non-native English speakers also experience less hours of services within the educational setting, as well as decreased access to the healthcare system (Amant et al., 2018). ASD is a "culturally-loaded diagnosis," meaning that the current diagnostic criteria were formulated referencing presentations seen most commonly in individuals that are male, white, and a part of Western culture (Matson et al., 2017). That is, the current criteria are not always applicable to people of color or individuals from other cultures, and therefore, delays diagnosis.

In 2023, Weitlauf et al., published a study that outlined 400 Black and multiracial families' experiences in the diagnostic process for ASD. Many families outlined several barriers to receiving a timely diagnosis. Specifically, the families reported that they had early concerns (e.g., prior to 18 months) regarding their child's development. However, they experienced roadblocks at the diagnostician, systemic and cultural level when attempting to access care. Most families saw more than one diagnostician before they received a diagnosis. 30.9% of the sample was diagnosed between the ages of 25-36 months, while a staggering 40.2% were diagnosed after the age of three. 34.4% of children were originally diagnosed with another disorder before receiving the ASD diagnosis.

Parents in this study also reported barriers associated with cultural differences (e.g., incongruence with diagnostician race), racism (e.g., the behavior was a "Black thing"). and stigma (e.g., diagnosticians not wanting to label the child, the parental shame associated with having a special needs child, etc.). Interestingly, the parents in this study also reported a delayed diagnosis due to diagnostician decisions, such as taking a "wait and see" approach, misunderstanding of the heterogeneity of ASD (e.g., the child was described as being "too smart"), attributing behavior to assigned sex (e.g., males lag behind females in social development), telling parents their child will grow out of it and setting delayed age points for evaluation (e.g., diagnosis at four years). Finally, system level barriers occurred, such as limited access to service and lacking knowledge and information about ASD.

Systematic exclusion of BIPOC families also occurs in research of ASD, thereby limiting the field's understanding of cultural impact on the presentation of ASD, as well as the ability to design evidence-based treatment for these communities. For example. Girolamo et al., (2022) outlined that neuroscience research systematically excludes individuals from BIPOC

communities because instruments and assessments are not normed for individuals with coarse or curly hair or dark skin. This leads to a fundamental underrepresentation of individuals from the BIPOC communities in ASD research, which heavily relies upon neurological data, which further marginalizes the BIPOC communities. Accordingly, efforts to streamline diagnosis through biological markers remains insufficient for BIPOC families.

Intersectionality of Race and Assigned Sex. The intersectionality, or when an individual identifies from multiple, traditionally underserved communities (Howard and Renfrow, 2014), of race and assigned sex further delays the diagnostic process. For example, Diemer and Gerstein (2022) theorize that Black females are "invisible" in the current ASD literature. This was empirically supported by Goldblum et al., (2023) who outlined the statistical relationship between assigned sex, race and ethnicity. Interestingly, when assigned sex was not accounted for a hierarchical regression model, BIPOC families were diagnosed at an earlier age than White families. However, when assigned sex was added to the regression model, the relationship changed. That is, females from Black, Asian and non-Hispanic White communities were diagnosed later than males in the same communities. This relationship highlights the fact that the diagnostic criteria was created utilizing primarily male, White patients, thereby further marginalizing females within BIPOC communities. As such, it is imperative that the intersectionality between assigned sex and race is accounted for when screening and assessing for ASD. This can be addressed by utilizing a culturally-responsive lens to interpret behavior and development, as opposed to the standard diagnostic criteria.

Disparities by Socioeconomic Status

In addition to racial and assigned sex disparities, significant challenges in the diagnostic process are also experienced by families from low-income households. Previous literature has

shown that individuals that come from low-income households receive a diagnosis significantly later then individuals that come from high income households (Martinez et al., 2018). Furthermore, families that come from high-income households report higher levels of satisfaction with the diagnostic process in general, and report taking less steps in obtaining a diagnosis (Goin-Kochel et al., 2006). Individuals that have higher income have better insurance coverage, which in turn allows for more choices in care and diagnosticians. As such, a free evaluation program for individuals that come from low-income backgrounds is also needed, as it can help bridge disparities in the healthcare system that prevent families from receiving a timely diagnosis.

Disparities by Parent Education

Another common barrier to diagnosis is the level of parent education, which is strongly associated with income (Fountain et al., 2011). Children with parents or caregivers that have higher education levels often receive diagnosis and treatment significantly earlier than children who have parents with lower levels of educational attainment. This difference is due to the number of resources that are associated with having a higher education, and therefore, a higher income. That is, individuals who come from higher education households often have more resources to navigate the diagnostic system and have better access to diagnosticians. Furthermore, the intersectionality between parent education and BIPOC status exacerbates the disparities in timely access to evaluation and treatment of ASD (Fountain et al., 2011). That is, BIPOC families that have lower levels of parent educational attainment have even longer wait-times compared to BIPOC families with higher levels of parent educational attainment, despite recognizing symptoms of ASD at similar ages.

Disparities by Neighborhood Resources

One tool that measures access to health care and overall needs at the community level is the Area Deprivation Index (ADI; Knighton et al., 2016). This tool utilizes data from the census, including education, income, employment, housing quality, etc. From there, census blocks are ranked on deprivation, which in turn measures their overall needs. To date, few autism studies have utilized the ADI to measure equity in diagnosis and treatment, despite it being an excellent tool for predicting healthcare and treatment for highly deprived neighborhoods.

Li et al., (2014) found that the incidence of ASD is highest in neighborhoods with the highest deprivation levels in Sweden. That is, children in high-deprivation neighborhoods are at a 59% increased risk of having ASD. Using the ADI, they found that the higher rates of ASD in the highly deprived neighborhoods occurred above and beyond individual- and family-level factors that influence diagnosis. This further highlights the need for more resources for individuals that are most underserved, as they have the highest rate and lowest resources to help support their needs.

Similar to the findings of Li et al.'s (2014) study, other studies conducted in Glasgow and France found that individuals in Glasgow were referred and diagnosed with ASD at a higher rate within the communities that had higher levels of deprivation (Campbell et al., 2014; Delobel-Ayoub et al., 2015). Other studies that have utilized the area deprivation index include examining disparities in physical health outcomes in ASD populations (Kelly et al., 2019; McGuinn et al., 2019; Magaña et al., 2023; Yu et al., 2024), as well as disparities in education (Roman-Urrestarazu et al., 2021; Absoud, 2022). In addition to this, studies in other regions have also highlighted the higher incidence of ASD within communities with higher deprivation levels, which in turn increases the risk of developing development disorders due to an impoverished environment (Emerson, 2012). These findings suggest that individuals in communities with

higher levels of deprivation are most at risk of having ASD, however, they also have the highest risk of delayed diagnosis due to systematic barriers.

Disparities by Cognitive Ability

An individual's cognitive ability also confounds the presentation of ASD, and, as such, complicates the diagnostic process further. First, males that have average cognitive ability have delayed diagnoses, often not occurring until they enter the school setting (Saban-Bezalel, Zachor, Ben-Itzchak, 2022). However, the opposite is true for females and BIPOC children. Females with ASD and co-occurring intellectual disability are often diagnosed later, as the comorbidity between intellectual disability and ASD particularly difficult to disentangle and requires longer evaluation time to conduct differential diagnostic assessments (Giarellii et al., 2010). Similarly, people of color that have co-occurring intellectual disability are also diagnosed significantly later and tend to be misdiagnosed compared to White people. That is, diagnosticians interpret presenting concerns for BIPOC children as behavioral issues and are more likely to give a behavioral disorder diagnosis than ASD.

In contrast, a growing number of studies have identified having higher verbal and cognitive ability as a predictor of a later diagnosis. Goodwin, Matthews & Smith (2019) found that children that were diagnosed after 5-years-old had significantly higher verbal IQ than their age-matched peers that were diagnosed before 5-years-old. In this study, parents and caregivers report of their first concerns were around the same age, however, the children with higher verbal ability were diagnosed later.

Barriers to Qualifying for Special Education Services under the Autism Category

Rates of the Autism *educational category* have increased over the last several years (Brock, 2006). However, this is variable based on the state in which the student resides. Interestingly,

Safer-Lichtenstein et al., (2020) found that Autism *educational category* rates varied by state and were moderated based on the state's political leanings. That is, states that had predominantly Democratic voters had higher rates of the Autism *educational category* compared to states that had predominantly Republican voters. Additionally, states with higher rates of the Autism *educational* category had lower rates of other educational categories, such as intellectual or learning disabilities. This change is likely due to an increased differentiation in evaluations between the Autism *educational category* and Intellectual Disability category.

Despite the growing prevalence of ASD in the greater community, Safran (2008) found that individuals with ASD are still underrepresented in the special education setting. Safran (2008) hypothesized that students with ASD may be underrepresented in special education because they are qualified for services under a different category than Autism. That is, they may be qualified for services under the category of Intellectual Disability, Emotional/ Behavioral or Learning Disability, etc. School psychologists use alternative eligibility categories because they do not feel comfortable giving the Autism *educational category* without a *medical diagnosis* (Pearson, 2008). This results in a persistent underrepresentation within schools and evaluation programs are needed to address said disparities.

As with the healthcare system, the COVID-19 pandemic also impacted access to special education services. During this time, students and their families lost access to resources through their schools and special education services, as school closures prevented teams from completing comprehensive special education evaluations per IDEA standards. Instead, evaluations were limited, as school psychologists and their teams had to rely on parent reports and behavioral observations to conduct special education evaluations (Latzer et al., 2021). Compliance with IDEA expectations became particularly challenging in high-poverty districts (Jackson and

Bowden, 2020), thus creating more barriers in already underserved populations. Hopkins et al,. (2023) found that, during the pandemic, students were under-identified in initial evaluations, thereby lowering rates of special education services compared to before the onset of the pandemic. This was especially true for students from BIPOC communities and low socioeconomic backgrounds, who faced significant delays in obtaining initial special education eligibility, further exacerbating inequities in these populations. Furthermore, mental health and psychiatric issues significantly increased due to the social isolation and school-closures during the pandemic, particularly in Black, Hispanic and low-income communities (Hawrilenko et al., 2021; Viner et al., 2022) Therefore, school psychologists and their colleagues faced a unique precedent due to this mental health crisis, thereby increasing their workload.

Identification Models for Underserved Populations

ASD diagnosticians have created culturally responsive intervention programs to improve diagnostic processes in underserved populations. For example, Feinberg et al., (2018) drew from the Patient Navigation Model (Freeman et al., 2011), which is traditionally used with cancer treatment, to provide an identification program for ASD specifically for BIPOC communities. In this study, families from traditionally underserved communities were randomly assigned to the Family Navigation Treatment Model (i.e., in-home visits and case management) or usual care (i.e., multiple visits to complete a comprehensive ASD evaluation within a healthcare setting). The Family Navigation program significantly increased access to services and ongoing care, as well as reduced wait time to diagnosis (Feinberg et al., 2018). This difference is due to the flexible nature of the model, as diagnosticians and treatment providers met families in their homes as opposed to requiring them to travel to the center, gave ongoing psychoeducation and, furthermore, provided culturally responsive, tailored interventions to meet the specific needs of

the families. Parents and caregivers also felt more support and less stress within the Family Navigation program compared to those within the usual care condition. Taken together, the current diagnostic model needs to be changed to reflect the needs of individuals from all populations, particularly those from traditionally underserved communities.

Two University Centers for Excellence in Developmental Disabilities (UCEDD) partnered with families to help foster advocacy for their children on the spectrum. Morgan et al., (2023) created a partnership between UCEDD and the Black families that they served, as well as stakeholders, to develop programs that are culturally responsive and meet the needs of the community. The UCEDD in Sacramento created Sankofa, which is a parent support group for Black parents with children with developmental disabilities. The group meets monthly to provide culturally responsive training to Black families and clinicians. In Wisconsin, the UCEDD created the Wisconsin Care Integration initiative, which is a partnership between the community and stakeholders. They created solutions to diagnostic and service barriers, such as providing funding to programs for Latinx families to help build advocacy and give the community a voice in their healthcare. Additionally, they held monthly meetings to create initiatives and programs to help decrease barriers. This brings the community together on a regular basis, thereby addressing concerns and barriers in real-time.

Importance of Early Intervention

Diagnosis alone is not sufficient for addressing the needs of the individual with ASD and their family. Subsequent treatment implemented by community-based providers is critical for overall well-being. Thus, after the diagnostic process is complete, evidence-based treatment should be implemented as quickly and early as possible. Early intervention has robust, positive long-term outcomes in increasing meaningful social-communication skills (Strain & Schwartz,

2001). One of the most common evidence-based treatments in ASD is applied behavioral analysis (ABA). Additionally, other modalities of treatment may be warranted, depending on the specific needs of the individual. For example, evidence-based social skill interventions are critical to increase prosocial behaviors and engagement with peers. Similarly, due to the inherent communicative deficits in ASD, the individual may benefit from speech therapy to increase social engagement, as well as to develop skills to effectively communicate their wants and needs (Yingling et al., 2020). Individuals with ASD often demonstrate sensory aversions or sensory-seeking behaviors, as well as fine motor delays that impact their daily functioning, which can be addressed with occupational therapy. Similarly, if the individual has gross motor delays, they may benefit from physical therapy. In addition to this, if the individual is school-aged and meets criteria for special education services, the school-based multidisciplinary team should work together to develop goals for the child's Individualized Education Program (IEP) and create a treatment plan that addresses the specific and individual needs of each child. Treatment goals should be operationally defined, measurable, and obtainable to help the child improve their social-communication skills, as well as any other areas of needed service.

Obtaining subsequent services after a diagnosis can be an arduous process that can decrease the quality of living for families. This process acts as a barrier to treatment, and includes difficulties with navigating insurance coverage, finding diagnosticians, and then experiencing long wait times (Thomas et al., 2007; Jones et al., 2017; Ning et al., 2019). Thus, the diagnostic team should provide ongoing case management or referrals for families in order to help them receive access to care. Additionally, it would be ideal to include evidence-based treatment, such as ABA, into educational programming at the school district to increase accessibility and inclusion for students from traditionally underserved populations.

One robust model of inclusive-education that the school-district may wish to implement in Part-C of IDEA (2004) is the Project for Developmentally Appropriate Treatment for Autism (Project DATA; Schwartz et al., 2004). This model for the education and treatment of ASD has five components, including 1) high-quality, inclusive early childhood program (i.e., integration of evidence-based practices into a preschool-program with children with and without developmental disabilities, 2) providing extended instructional time (i.e., increase the number of hours of school-based services), 3) technical and social support for families (i.e., providing home-based services, helping coordinate resources, providing parent support groups, etc), 4) collaboration and coordination across services (i.e., facilitate a continuum of care with outside services that the families pursued) and, 5) transition support (i.e., providing resources and support as children exit the preschool program). Project DATA demonstrated substantial gains across developmental domains, reduced parent stress, and increased parent satisfaction with treatment. Implementation of a program similar to that of Project DATA within Part C of IDEA (2004) would provide families with the opportunity to place their children in an inclusive educational setting while receiving high-quality, evidenced-based treatment to promote social-communicative and functional skills.

Purpose of the Study

Despite these initiatives, few programs have been created to help increase services to underserved populations, thereby increasing diagnostic delay. This can be explained by a lack of studies that have examined the factors associated with diagnostic delay using large-scale data. To date, few studies have modeled how the availability of resources (e.g., through area deprivation index) impacts diagnostic age, along with the other factors previously established in the literature. This is a critical violation of statistical assumptions, as it would be impossible to

disentangle the impact of individual predictors of diagnostic age without accounting for availability of resources within the community. Therefore, the purpose of this study is to describe the relationship between predictors associated with diagnostic age, while also looking at how access to services based on location also influence diagnostic age. Furthermore, this study aims to highlight the role of school psychologists in addressing barriers to ASD diagnosis for underserved communities.

The present study is the first to examine the relationship between the area deprivation index (e.g., income, education, access to resources) and other predictors associated with the diagnostic age in the United States. This study also utilizes data from a large-scale sample across 31 sites, providing a robust representation of current trends in the United States. By using linear and logistic regression, this study accounts for variations in the data that may be influenced by predictors such as an individual's location and access to community resources, thereby strengthening the validity of the findings. The study outlines the importance of school psychologists' involvement in ASD identification for underserved communities that experience systemic and systematic barriers to diagnosis.

Furthermore, the purpose of the present study is to outline implications for the practice of school psychologists within the field of ASD identification. By utilizing the data from this study, school psychologists can partner with community stakeholders to create a program that can identify individuals most at risk of a delayed diagnosis. School psychologists can reach students in these populations, as they are in an accessible setting that provides funding for identification of all children with disabilities (e.g., Child Find, IDEA, 2004). Findings from this study will have theoretical implications that school psychologists can partner with community stakeholders to create an ASD identification models to be utilized within school system, providing accessible

care for individuals from communities that are at most-risk of late identification due to a lack of resources.

Research Questions

Given the paucity of research about the contextual and individual factors involved in ASD diagnosis and identification, and especially the involvement of school-based teams in identifying ASD, this study will utilize the national longitudinal data collected from 2013-2023 by the Simons Powering Autism Research for Knowledge (SPARK) study to evaluate the following research questions.

1) (a) To what extent does a child's geographic area deprivation level (by state) predict **ASD diagnosis age**? (b) Controlling for children's geographic area deprivation levels, to what extent does year of diagnosis as well as sociodemographic individual characteristics uniquely predict ASD diagnostic age? (c) Are there interactions among predictors (i.e., moderators) in predicting diagnosis age??
2) (a) To what extent does a child's geographic area deprivation level (by state) predict the **likelihood of a school-based team identifying a child as having ASD**? (b) Controlling for children's geographic area deprivation levels, to what extent does year of identification well as sociodemographic individual characteristics, including age of diagnosis (e.g., identification), uniquely predict the likelihood of a school-based team identifying a child aas having ASD? (c) Are there interactions among predictors, including identification age, in predicting the likelihood of a school-based team identifying a child as having ASD?

CHAPTER 3: METHOD

Participants

Data for the current study was drawn from the Simons Powering Autism Research for Knowledge (SPARK) study database. The SPARK study is a large-scale, nationwide study across 31 sites designed to identify underlying genetic mutations associated with autism spectrum disorder (ASD). Individuals with ASD and their biological family members (*N* =328,973, ages 1 month to 85 years) were invited to participate. (Note that site membership information was not made available for the present study, however). Inclusion criteria for the original SPARK study comprised the following: 1) at least one individual in a family (e.g., "proband") must have had a clinical diagnosis of ASD that meets criteria outlined in the Diagnostic and Statistical Manual, 5th Edition (DSM-5, APA 2022), or, any of the disorders under the umbrella of Pervasive Developmental Disorders in the DSM-IVR (i.e., Autism, Pervasive Developmental Disorder, Not Otherwise Specified, Asperger's Disorder, Rett syndrome or Childhood Disintegrative Disorder; APA, 2000); and 2) families must have been able to read and write in the English language, as surveys were only available in English.

For the present study, only data from probands (e.g., the participant with ASD), and only participants ages 18 months to 17:11 years, were included for analysis (*N* = 38,233). This specific age range was selected because: 1) there is a lack of reliability for ASD diagnosis below 18 months old (Stone et al., 1999), and 2) the research questions pertain to children and adolescents. Additionally, probands who were diagnosed before the criteria shift in the DSM-5 (e.g., diagnostic year 2012 and earlier) were excluded (*n* = 11,527) to ensure a consistent definition of diagnosis. Further, although the average number of participants with ASD per family in the sample was 1.01 (i.e., most participants did not have an additional family member participating in the study), siblings with ASD were also excluded (*n* = 513) to ensure the assumption of independence for statistical. Finally, validity checks of the variables used in

analyses resulted in the exclusion of analyses n = 8,186 participants (i.e., an ASD diagnosis of "rescinded" or "refuted", and values reported that were not within the range of the variables' defined values). The final sample used in analyses was N = 18,518, with n = 3,819 (21%) females, and an average age of M = 80.15 months (SD = 38.53).

Procedures

In the original SPARK study, participants were recruited from one of the 31 clinical sites that specialize in ASD diagnosis and research or through online advertisements. All sites obtained approval for Human Subjects Research from their respective Institutional Review Boards. Once consented, participants were invited to the SPARK portal, which is an online platform for completing questionnaires. All participants were assigned an individual and family ID to protect confidentiality. Additional measures to protect confidentiality include keeping identifying information separate from participant results. The present study obtained approval from University of Washington institutional review board (IRB), as well as authorization from the Simons Foundation Autism Research Initiative (SFARI), and de-identified data was provided by SFARI to the principal investigator for analysis.

Measures

Parents and caregivers filled out the selected surveys online through the SPARK study portal. For this study's analyses, variables were drawn from the *Background History Questionnaire* file, the *Individual's Registration* file, the *Roles Index* file, the *Social-Communication Questionnaire* (SCQ; Rutter et al., 2003) file, and the *Area Deprivation Index* (ADI; Knighton et al., 2016). More details about each file are given below.

Background History Questionnaire

This survey was created by the SPARK study team. It consists of 117 questions that measure demographic information, treatment history and social history. For the present study, the following variables were used: subject ID, family ID, sex, age at evaluation, and family history of ASD.

Individuals Registration Survey

This survey was also created by the SPARK study team and consists of 45 questions measuring individual factors related to ASD diagnosis. For the present study, the following variables were used either for filtering the data or for analyses: diagnosis age (e.g., age of identification of ASD by a professional, either within a medical or educational setting), ASD validity flag, diagnosis source, race, and cognitive impairment.

Roles Index

This data file includes 37 variables about the "role" of the participant: as proband or as a related family member; for relatives, it includes what their relationship is to the proband. For the present study, these data were used to filter the sample to probands only.

Social Communication Questionnaire

The Social-Communication Questionnaire (SCQ; Rutter et al., 2003) was created as a screening tool for ASD diagnosis. It consists of 40 yes/no items used to screen for ASD. In previous research, the SCQ total score has shown strong reliability in discriminating between children with a diagnosis of ASD and typically developing peers (Chandler et al., 2007). Thus, for the present study, the total SCQ score was used to represent ASD severity.

Area Deprivation Index

The Area Deprivation Index (ADI; Kind et al., 2014) is a tool used to measure levels of economic deprivation of geographic areas, much like socioeconomic status indices are created to

measure economic deprivation for individuals. Specifically, it factors in geographic-level education, income, employment, and housing quality levels. Neighborhood blocks from census tracts are ranked on deprivation levels and then transformed into deciles for both state- and national-level deprivation indices. In the present study, because site-specific information is not available, I used this variable both as a proxy for the degree to which a family has access to community resources, like healthcare systems, as well as to control for the potential non-independence of individual characteristics by site.

Analytic Approach

Research Question 1: Predicting Age of ASD Diagnosis

To evaluate the first research question regarding the prediction of age of ASD diagnosis (e.g., age at which a child was first identified as having ASD), I used multiple linear regression with sequential predictor entry to model **ASD diagnosis age** (e.g., when a professional team first identified a child as having ASD) using the following variables: **area deprivation index (ADI) state-based deciles**, which is a categorical variable with ten decile increments that were transformed into a set of nine effect-coded predictors (higher deciles = higher levels of deprivation/fewer resources; effect-coded for modeling with the first decile as the reference category); **ASD diagnostic year**, mean-centered at 2019 to represent the historical shift in healthcare due to the COVID-19 pandemic (recalling that the sample spans years 2013-2023); **family history of ASD status**, where 1 = participants who had a family member with ASD; **cognitive impairment status**, where 1 = cognitive delay (effect-coded for modeling); **SCQ Severity**, which is the total score from the SCQ where higher scores indicate greater ASD severity (standardized into *z*-scores for modeling); participant Black, Indigenous, and People of Color **(BIPOC) status**, where 1 = yes (effect-coded for modeling); and participant **female status,** where 1 = yes (effect-coded for modeling).

Importantly, the dependent variable (age of ASD diagnosis) was severely right-skewed, so it was transformed into its natural logarithm for modeling to help ensure that the traditional model assumptions of linearity and normality were tenable. The first block of predictors included the set of effect-coded ADI deciles 2-10 in order to estimate the variance explained by the socioeconomic status of the areas from which participants were drawn. The second block added all of the other predictors, controlling for ADI decile. The third and final block added 2-way interactions between diagnosis year and the other predictors in the second block. Below is the final multiple linear regression model with all terms included.

$$\begin{aligned} LN(\text{Diagnosis Age in Months}) = {} & b_0 + b_1*\text{ADI State Decile2} + b_2*\text{ADI State Decile3} \\ & + b_3*\text{ADI State Decile4} + b_4*\text{ADI State Decile5} + b_5*\text{ADI State Decile6} \\ & + b_6*\text{ADI State Decile7} + b_7*\text{ADI State Decile8} + b_8*\text{ADI State Decile9} \\ & + b_9*\text{ADI State Decile10} + b_{10}*\text{DxYear} + b_{11}*\text{FamilyHx} + b_{12}*\text{CogImp} \\ & + b_{13}*Z\text{SCQSeverity} + b_{14}*\text{BIPOC} + b_{15}*\text{Female} \\ & + b_{16}*\text{DxYear*FamilyHx} + b_{17}*\text{DxYear*CogImp} + b_{18}*\text{DxYear*}Z\text{SCQSeverity} \\ & + b_{19}*\text{DxYear*BIPOC} + b_{20}*\text{DxYear*Female} + b_{21}*\text{FamilyHx*CogImp} \\ & + b_{22}*\text{FamilyHx*}Z\text{SCQSeverity} + b_{23}*\text{FamilyHx*BIPOC} \\ & + b_{24}*\text{FamilyHx*Female} + b_{25}*\text{CogImp*}Z\text{SCQSeverity} + b_{26}*\text{CogImp*BIPOC} \\ & + b_{27}*\text{CogImp*Female} + b_{28}*Z\text{SCQSeverity*BIPOC} \\ & + b_{29}*Z\text{SCQSeverity*Female} + b_{30}*\text{BIPOC*Female} + e \end{aligned}$$

An alpha of .05, 2-tailed, was used for all statistical tests. To assess the practical value of the results, squared semi-partial correlations were computed as the effect size for each coefficient using the parameter estimate *t*-test statistic, model residual *df*, and model total R^2 (e.g., Aloe & Thompson, 2013) as follows.

$$sr^2 = ((t^2/(t^2 + df))*(1 - R^2))/(1 - (t^2/(t^2 + df)))$$

Data visualization of model-predicted values was implemented using the 'ggplot2' package (Wickham, 2016) (with interaction term predicted values extracted with the 'effects' package (Fox & Weisberg, 2019)).

Research Question 2: Predicting Likelihood of ASD Diagnosis by a School-Based Team

The same variables used to evaluate research question 1 were used in testing research question 2, but with three adaptations. First, the dependent variable for this analysis was a binary variable of whether or not a **school-based team gave the diagnosis (e.g., identified the child as having ASD)**, where 1 = yes and 0 = other provider made the diagnosis (e.g., psychologist, physician, health team). Second, in addition to the previous predictors, **age of diagnosis** was also included as a predictor. However, because age was severely skewed (as previously mentioned), and to further boost interpretability of the model results particularly with respect to ages related to public education bands, I created a set of four age groups: Age Band1 = 18 months to 2.9 years (i.e., early childhood, birth-to-three), Age Band2 = 3.0 to 4.9 years (preschool), Age Band3 = 5.0 to 11.9 years (elementary school), and Age Band4 = 12.0 to 17.9 years (middle/high school). I then effect-coded these groups into a set of three predictors with Age Band1 as the reference category. The third difference between my model for this research question and the previous one was that I used a logistic, rather than linear, regression model. (Blocks of predictors were kept the same as before, where the first block included the ADI deciles, the second block

included the socio-demographic predictors, and the final block included interaction terms among the predictors in the second block.) The final multiple logistic regression model was as follows.

$$\begin{aligned}
\text{LN}(\text{Pr}(\text{School-Based Team Diagnosis})) = {} & b_0 \\
& + b_1*\text{ADI State Decile2} + b_2*\text{ADI State Decile3} \\
& + b_3*\text{ADI State Decile4} + b_4*\text{ADI State Decile5} + b_5*\text{ADI State Decile6} \\
& + b_6*\text{ADI State Decile7} + b_7*\text{ADI State Decile8} + b_8*\text{ADI State Decile9} \\
& + b_9*\text{ADI State Decile10} + + b_{10}*\text{Age Band2} + b_{11}*\text{Age Band3} + b_{12}*\text{Age Band4} \\
& + b_{13}*\text{DxYear} + b_{14}*\text{FamilyHx} + b_{15}*\text{CogImp} \\
& + b_{16}*Z\text{SCQSeverity} + b_{17}*\text{BIPOC} + b_{18}*\text{Female} \\
& + b_{19}*\text{Age Band2}*\text{DxYear} + b_{20}*\text{Age Band2}*\text{FamilyHx} \\
& + b_{21}*\text{Age Band2}*\text{CogImp} + b_{22}*\text{Age Band2}*Z\text{SCQSeverity} \\
& + b_{23}*\text{Age Band2}*\text{BIPOC} + b_{24}*\text{Age Band2}*\text{Female} \\
& + b_{25}*\text{Age Band3}*\text{DxYear} + b_{26}*\text{Age Band3}*\text{FamilyHx} \\
& + b_{27}*\text{Age Band3}*\text{CogImp} + b_{28}*\text{Age Band3}*Z\text{SCQSeverity} \\
& + b_{29}*\text{Age Band3}*\text{BIPOC} + b_{30}*\text{Age Band3}*\text{Female} + b_{31}*\text{Age Band4}*\text{DxYear} \\
& + b_{32}*\text{Age Band4}*\text{FamilyHx} + b_{33}*\text{Age Band4}*\text{CogImp} \\
& + b_{34}*\text{Age Band4}*Z\text{SCQSeverity} + b_{35}*\text{Age Band4}*\text{BIPOC} \\
& + b_{36}*\text{Age Band4}*\text{Female} \\
& + b_{37}*\text{DxYear}*\text{FamilyHx} + b_{38}*\text{DxYear}*\text{CogImp} + b_{39}*\text{DxYear}*Z\text{SCQSeverity}
\end{aligned}$$

$$+ b_{40}*\text{DxYear}*\text{BIPOC} + b_{41}*\text{DxYear}*\text{Female} + b_{42}*\text{FamilyHx}*\text{CogImp}$$

$$+ b_{43}*\text{FamilyHx}*Z\text{SCQSeverity} + b_{44}*\text{FamilyHx}*\text{BIPOC}$$

$$+ b_{45}*\text{FamilyHx}*\text{Female} + b_{46}*\text{CogImp}*Z\text{SCQSeverity} + b_{47}*\text{CogImp}*\text{BIPOC}$$

$$+ b_{48}*\text{CogImp}*\text{Female} + b_{49}*Z\text{SCQSeverity}*\text{BIPOC}$$

$$+ b_{50}*Z\text{SCQSeverity}*\text{Female} + b_{51}*\text{BIPOC}*\text{Female}$$

As with the linear regression model, an alpha of .05, 2-tailed, was used for all statistical tests. To assess the practical value of the results, however, I use odds ratios and their 95% confidence intervals since logistic regression models do not have residual error like linear regression models.

CHAPTER FOUR: RESULTS

Research Question 1: Predicting Age of ASD Diagnosis

Descriptive Statistics

Means, standard deviations, and zero-order correlations among all variables are given in Table 1. For brevity, only significant correlations between the dependent variables and predictors are summarized here. First, with respect to state area deprivation index (ADI) deciles, autism spectrum disorder (ASD) diagnosis age (log-transformed) was negatively correlated with deciles 2 and 6 (ps < .001) and positively correlated with deciles 7 and 9 (ps < .001), indicating that participants from more deprived areas tended to be associated with older ages of diagnosis, and vice versa.

Second, diagnosis age was also positively correlated with diagnosis year since the COVID-19 pandemic (p < .001), meaning that diagnosis age increased with each year post-pandemic. To help visualize this relationship, Figure 1 displays a heat map of ASD diagnosis age by year of the study; as can be seen, there was a greater number of younger children that had been diagnosed post-pandemic (see especially the red pattern in 2021).

In terms of individual characteristics, family history of having a relative with ASD was positively correlated with diagnosis age (p < .001), indicating that probands who had a family member with a diagnosis of autism spectrum disorder had a higher diagnosis age compared to those without. Similarly, cognitive impairment status was also positively correlated with diagnosis age (p < .001), where individuals who had cognitive delays tended to receive a diagnosis later than individuals that do not have a cognitive delay. SCQ severity was negatively correlated with diagnosis age (p < .001), indicating that individuals with higher levels of ASD symptoms received earlier diagnoses. In contrast, BIPOC status was negatively correlated with diagnosis age (p < .001), indicating that, on average, individuals who identified as being BIPOC

received diagnoses at an earlier age than individuals that identified as being White. Finally, female status was positively correlated with diagnosis age, indicating that females, on average, received diagnoses at a later age compared to males ($p < .001$).

Multiple Linear Regression Results

Overall model performance. Table 2 reports the multiple linear regression model results for each block of predictors added. Model 1, which included the set of area deprivation index state level predictors, accounted for <1% of variance in the log of diagnosis age, $R^2 = .001$, $p = .378$. This indicates that the set of ADI deciles did not account for significant variance in age of diagnosis (recall age was log-transformed). Model 2, which incorporated the block of focal socio-demographic predictors, accounted for a total of 2.5% of the variance in diagnosis age, which was significant ($F(15, 18{,}502) = 77.14$, $p < .001$). Finally, Model 3, which added two-way interaction terms between the focal predictors in the model, accounted for 3.1% of the variance in diagnosis age (0.6% more than Model 2); this too was significant ($F(30, 18{,}487) = 19.4$, $p < .001$).

Coefficients. To interpret the unique effects of the predictors, I focused on the final model results (last set of columns in Table 2). In the final model, all of the individual characteristic variables were uniquely predictive of age of diagnosis, with the exception of family history of ASD. Below I detail the meaning of each of the significant regression coefficients, starting with the intercept.

Given the manner with which predictors were coded, the **intercept** estimate indicated that, before the onset of the COVID-19 pandemic in 2019 (where year of diagnosis was centered), the estimated log-transformed ASD diagnosis age averaged 3.87 units. When exponentiated, this value translates to 47.99 months of age, or approximately 4 years of age.

When examining the **ADI decile effects**, model results largely mirrored what we observed in the zero-order correlations – namely that participants from a region with an ADI decile 2 were predicted to have a 0.03-unit lower diagnosis age compared to the mean diagnosis age (i.e., exp(3.87-0.10) = 46.62 months compared to the mean of 47.99 months), holding all other values constant (p = .006, sr^2 = <.001) and individuals from an ADI decile 9 had a 0.03-unit greater diagnosis age compared to average (i.e., exp(3.87-0.10) = 49.40 months compared to the mean of 47.99 months), holding all else constant (p = .028, sr^2 = <.001).

Diagnosis year since COVID-19 was also a significant predictor of age of diagnosis. Specifically, age of diagnosis was predicted to increase by 0.01 units for each year after 2019 (i.e., the pandemic onset), holding all else constant (p < .001, sr^2 = .001). This indicates that, all else being equal, participants who were diagnosed in 2020 (one year after the pandemic onset) were predicted to be diagnosed with ASD at exp(3.87+1*.01) = 48.57 months old compared to the pre-pandemic 2019 mean diagnosis age of 47.99 months. In the same vein, participants who were diagnosed in 2021 (two years after 2019) were predicted to be diagnosed with ASD at exp(3.87+2*.01) = 49.16 months old compared to the 2021 age of 47.99 months. In contrast, participants who were diagnosed in 2017 (two years *before* 2019) were predicted to be diagnosed with ASD at exp(3.87–2*.01) = 46.85 months old (lower) than the 2019 age of 47.99 months.

Cognitive impairment status has the largest effect on diagnosis age in the model. Specifically, those who identified as having cognitive impairment were predicted to be diagnosed with ASD at exp(3.87+0.10) = 53.04 months of age compared to the mean age of 47.99 months, all else held constant (p < .001, sr^2 = .007). Conversely, those who did not have a cognitive impairment were predicted to be diagnosed at a younger age, of exp(exp(3.87–0.10) = 43.42 months.

Autism severity (SCQ) was also uniquely predictive of diagnosis age: for every standard deviation increase in severity, there was a predicted decrease of 0.05 units in age of ASD diagnosis (log-transformed), all else held constant ($p < .001$, $sr^2 = .003$). This indicates that children with greater severity were predicted to be diagnosed earlier at an age of exp(3.87–0.05) = 45.47 months, compared to the mean age of 47.99 months.

In addition to the other main effects previously described, both **BIPOC status** and **female status** were also each uniquely predictive of age of diagnosis, all else held constant. Whereas BIPOC students were predicted to be diagnosed at a younger age than average of exp(3.87–0.05) = 45.47 months (ps < .001, sr^2s = .003), female students were predicted to be diagnosed at an older age than average of exp(3.87+0.02) = 48.86 months ($p = .025$, $sr^2 = <.001$).

Some of these main effects, however, are qualified by **interactions** detected in the final model. Most notably, the effect of cognitive impairment status on ASD diagnosis age (i.e., those with cognitive impairment were diagnosed at an older age) was moderated by diagnosis year, family history of ASD, BIPOC status, and female status. The directionality of the interactions indicate that the older-age-effect was even greater for children with family members who had ASD, as well as those who identify as BIPOC or female.

The remaining three significant interactions were between ASQ autism severity and diagnosis year, BIPOC status, and female status. Recalling that the main effect of autism severity was negative (i.e., increased severity predicted younger age of diagnosis), the pattern of results indicates that the relationship became more negative at the pandemic onset (after 2019) as well as for female children (see Figure 2); the relationship was weaker, however, for BIPOC children (see Figure 3).

Research Question 2: Predicting Likelihood of ASD Diagnosis by a School-Based Team

Descriptive Statistics

Descriptive statistics were provided previously in Table 1. To avoid redundancy, only relations among predictors and ASD diagnosis by a school-based team are discussed here. In terms of contextual factors, ADI deciles 1 and 7 were found to be negatively correlated with receiving a school-based diagnosis (*p*s < .001) while deciles 2, 8 and 10 were positively correlated with receiving a school-based diagnosis (*p*s < .001). This suggests a strong amount of variability among deciles unrelated to the increase or decrease in resource levels in terms of probability of a school-based ASD diagnosis – in other words, it is likely that there are unmeasured site-specific nuances giving rise to the relations between ADI deciles and school-based ASD diagnosis likelihood. Another contextual factor, diagnosis year since the pandemic onset, was also correlated with receiving a school-based diagnosis; this relation was negative, indicating that individuals with ASD were diagnosed less often by school-based teams after 2019 (e.g., during and after the pandemic). The heat map in Figure 4 depicts this relationship by age.

Last, all individual characteristics were significantly related to the dependent variable. Age of diagnosis, family history of ASD status, SCQ severity of autism, cognitive impairment status, and BIPOC status were each positively correlated with school-based ASD diagnosis (*p*s < .001), whereas female status was negatively correlated with school-based diagnosis ($p < .001$).

Multiple Logistic Regression Results

Overall model performance. The multiple logistic regression model results are provided in Table 3. In the first model with only the ADI decile groups, there was no significant improvement over the null model of no predictors, $\chi 2(df = 9, N = 18{,}526) = 9.24$, $p = .416$ (Nagelkerke pseudo-R2 = .00). Sensitivity (correct classification of participants who were diagnosed by a school-based team) was 0%, specificity was 100% (correct classification of participants diagnosed by a non-school-based professional), and the overall accuracy rate was

69%. Model 2, which added the focal predictors (main effects), significantly improved upon Model 1, $\chi 2(df = 9, N = 18{,}499) = 780.85$, $p < .001$ (Nagelkerke pseudo-R2 = .06). Classification improved minimally, where sensitivity increased to 4% and specificity decreased to 98% (the overall classification accuracy rate remained 69%). Model 3, which added two-way interaction terms among the focal predictors, significantly improved upon Model 2, $\chi 2(df = 33, N = 18{,}466) = 120.21$, $p < .001$ (Nagelkerke pseudo-R2 = .07). Prediction accuracy improved to 99% but sensitivity decreased slightly from 4% to 3% (overall classification accuracy rate remained the same at 69%). The logistic regression model exhibited low sensitivity in identifying children diagnosed with ASD by school-based teams, while demonstrating high accuracy in predicting those diagnosed by other professionals. This is likely in part due to the relatively lower number of children diagnosed by a school-based team in the sample (31%).

Coefficient results. To interpret the unique effects of the predictors I again focus on the final model results (last set of columns in Table 3). First, the intercept estimate indicated that the average likelihood of receiving a school-based diagnosis was −1.10 logits (which translates to a mean predicted probability of 33% across the sample, closely matching the simple sample mean of 31%).

Several main effects significantly predicted the likelihood of receiving a school-based diagnosis, including ADI deciles, age bands, year of diagnosis, BIPOC status, and female status. All other things being equal, participants from a region with an **ADI decile** 5 had an odds of receiving a school-based diagnosis that were 1.12 times greater compared to the sample mean (i.e., higher odds of diagnosis; $p = .005$), whereas individuals from a region with ADI decile 7 had an odds of diagnosis by a school-based team that were 0.87 times that of the mean odds (i.e., lower odds; $p = .008$).

Age band was also a significant predictor. All else held constant, children in the preschool age group had odds that were 1.15 times greater than average to be diagnosed by a school-based team ($p = .039$) as were children in elementary school (1.32 times greater odds, $p < .001$). On the other hand, children in the middle or high school age range were not more likely to be diagnosed by a school-based team than other professionals ($p = .929$). **Year of diagnosis** since 2019 was also significant, with each year after 2019 associated with a lower likelihood of a school-based diagnosis by 0.92 times the odds of average odds, all else held constant ($p < .001$). Diagnosis age and time period effects on likelihood of a school-based ASD diagnosis, however, were qualified by the 2-way **interactions** detected in the final model. In particular, the negative association between year of ASD diagnosis and likelihood of a school-based team making the diagnosis depended on age band (see Figure 5). As can be seen in figure 5, the likelihood of younger children being diagnosed by school-based teams decreased over time, with a most pronounced decrease for preschoolers. Comparatively, the likelihood of diagnosis by a school-based team remained quite stable over time for middle-school and high-school ages.

In terms of individual demographic characteristics, the model results showed that children with **BIPOC status** were associated with a greater likelihood of receiving a school-based diagnosis compared to average ($p < .001$), and this effect was not qualified by age band (Figure 6) or any other factor as indicated by the lack of interactions with BIPOC status, all other things being equal (ps > .05).

Finally, we observed that **female** children were less likely to receive a school-based diagnosis compared to average ($p = .032$), all other things held constant. While this relation did not depend on age band differences (see Figure 7; interaction ps > .05), the female effect was qualified by its interaction with SCQ autism severity ($p = .005$): females with greater autism

severity were more likely to be diagnosed by a school-based team compared to females with lower autism severity (see Figure 8).

CHAPTER FIVE: DISCUSSION

The purpose of the present study was to model the barriers within the current diagnostic system for autism spectrum disorder (ASD), using nationally representative data from the SPARK study. This study had two primary objectives: First, it aimed to identify the individual and socioeconomic factors that predict the age at which a child receives an ASD diagnosis. Several systemic and systematic barriers contribute to delays in diagnosis, including race (e.g., BIPOC) being female, having a cognitive impairment, and residing in areas with fewer resources, as measured by the Area Deprivation Index. Additionally, the COVID-19 pandemic also impacted the timing of diagnosis due to the unprecedented demand on healthcare providers and limited ability to assess for ASD. Second, this study examined the role of school psychologists in the identification of ASD, particularly for underserved communities. Specifically, it assessed the probability of receiving a diagnosis from a school-based team based on individual and socioeconomic factors. Findings from this study have important implications for practice, highlighting the need to develop targeted programs that improve timely and accurate ASD diagnosis, both within schools and the broader healthcare system.

Question 1

The first research question aimed to measure the relationship between individual and socioeconomic factors and age at which an individual received an ASD diagnosis. Specifically, the study examined the systematic relationship between individual factors (e.g., BIPOC status, female status, diagnosis year, cognitive impairment, family history of ASD, symptom severity) and socioeconomic factors (e.g., Area Deprivation Index State Decile) and age of diagnosis. Linear regression was used to model how the focal predictors and their interactions uniquely predicted variation in diagnostic age. The final model included ADI state decile (a measure of

resources based on location), diagnostic year (centered around 2019, prior to the onset of the COVID-19 pandemic), family history status, cognitive impairment status, severity, BIPOC status, and female status, along with interactions between the focal predictors.

Results indicated that ADI state decile was statistically significant for decile two when compared to the mean, with individuals from decile two being diagnosed earlier. Additionally, individuals in state decile nine were diagnosed later than the mean. Although individuals in deciles two through five were diagnosed earlier than the mean, and those in deciles seven through ten were diagnosed later, only the differences in deciles two and nine were statistically significant. Individuals with more resources, as defined by the ADI (e.g., those in decile 2) receive, on average, earlier diagnoses than those with lower resources (e.g., those in Decile 9). This is consistent with the literature that the higher the income, education and resources, the earlier the diagnosis (Parikh et al., 2018).

Diagnostic year also significantly predicted diagnosis age. Individuals diagnosed after in 2020 and beyond, which was during the COVID-19 pandemic, were diagnosed later than the mean. This aligns with the present literature, as the pandemic's disruption of the healthcare system limited access to diagnostic services and increased wait times (Spain et al., 2022). Furthermore, previous research indicated that clinicians faced challenges in accurately diagnosing ASD via telehealth services during quarantine periods, as assessment tools were not validated for online use (McNally et al., 2021). Additionally, insurance limitations on telehealth-based assessments further delayed diagnoses within the autism community. Thus, diagnosis was delayed post-pandemic.

Cognitive impairment status also predicted diagnostic age, with individuals who had cognitive delays receiving diagnoses later than the mean. This finding aligns with existing literature, which suggests that individuals with cognitive impairments are often diagnosed with other disabilities before receiving an ASD diagnosis. Conversely, severity of symptoms was significantly associated with diagnosis age, with individuals exhibiting higher severity levels receiving earlier diagnoses. This result is expected, as more severe symptoms are easier to detect and often manifest at an earlier age (Mandell et al., 2005). Developmentally, individuals with more severe symptoms may demonstrate fewer social behaviors, such as joint attention and social smiling, making their symptoms more noticeable to families and professionals. Taken together, the complexity of the presentation of symptoms is an important predictor of the timing of diagnosis.

BIPOC status significantly predicted diagnostic age, however, the direction of the effect was not consistent with previous literature. In the present study, individuals from BIPOC communities were diagnosed, on average, earlier than the mean. This may be due to changes in the DSM-5-TR (APA, 2022), which streamlined diagnostic criteria to improve clarity and consistency across clinicians, especially in underserved communities. Additionally, increased efforts within the field to improve access to services for BIPOC communities may have contributed to this trend. It is important to note that, per descriptive statistics, the average age of diagnosis for the sample is approximately 4.5 years old. The trend in earlier diagnosis for BIPOC individuals, compared to the mean of the sample, is encouraging for the greater community and suggests the field is trending toward earlier diagnosis. This finding is starkly different than the literature that demonstrates BIPOC individuals are diagnosed much later than White individuals (Mandell et al., 2002). However, the clinical significance of this difference is less meaningful in

the broader context, as diagnosis still occurs much later than the best practice recommendation of 18 months (Baird et al., 2000). This highlights a persistent gap in early identification and intervention across all groups that must continue to be addressed.

Finally, female status was a significant predictor of diagnostic age, with females receiving diagnoses at a later age compared to the mean. This finding is consistent with existing literature, which suggests that females are often diagnosed later due to a clinical presentation of symptoms that are more subtle and more difficult to detect (Hiller et al., 2014; Young, et al., 2018). The diagnostic criteria for ASD was largely formulated using the presentation of symptoms most commonly seen in (white) males, as males are diagnosed with ASD more frequently than females. In contrast to males, females frequently exhibit a different subset of symptoms, characterized by stronger social-communication skills and more social-reciprocity (Hiller et al., 2014; Young, et al., 2018). Additionally, females are more likely to engage in masking behaviors. As a result, their symptoms may be more subtle and less readily recognized, leading to delayed diagnosis. Taken together, the complexity of the symptomology that females exhibit requires specialized training in precision diagnosis.

Interestingly, cognitive impairment and severity levels significantly interacted with several other key variables, suggesting that these factors are important predictors of diagnostic age. Specifically, cognitive impairment interacted with diagnostic year, with individuals with cognitive delay that were diagnosed after the pandemic having a later diagnosis compared to the mean. This finding may likely be due to the limitations of telehealth assessments, which contributed to delays. That is, cognitive assessments are not validated for online administration. As a result, children with cognitive impairments may have had to wait for in-person evaluations

to conduct differential diagnosis, which, in turn, delayed their ASD diagnosis. Cognitive impairment status also interacted with family history, with individuals who had both cognitive impairment and a family history of ASD being diagnosed earlier than the mean. This trend makes sense, as families with a history of ASD may be more familiar with developmental concerns and more adept at identifying early signs of autism.

Additionally, cognitive impairment status interacted with BIPOC status. Individuals from BIPOC communities with reported cognitive impairment were diagnosed later than the mean. This finding aligns with existing literature regarding the intersectionality of disabilities and BIPOC status, which suggests that BIPOC children are often misdiagnosed with behavioral or intellectual disabilities before receiving an ASD diagnosis (Mandell et al., 2009). Furthermore, BIPOC status interacted with severity, with BIPOC individuals exhibiting higher levels of ASD severity being diagnosed later than white individuals with comparable severity. This is notable, as severity is typically a predictor of an earlier diagnosis. This trend highlights the need for greater awareness and understanding of ASD presentations within BIPOC communities, as symptoms may be misattributed to behavioral disorders or other developmental disorders.

Cognitive impairment status also interacted with female status, with females who had cognitive impairment being diagnosed later than the mean. Conversely, females with higher severity levels were diagnosed earlier than the mean. This suggests that highly severe symptoms may reduce the masking effect often seen in females, making their presentation more consistent with male diagnostic criteria and, therefore, easier to identify. However, it is perplexing that the cognitive impairment status interaction with female status resulted in an increased diagnostic age, above and beyond the main effects. That is, it appears that for individuals that are not White

males and that have complex presentations are, on average, diagnosed later. As with BIPOC communities, these findings emphasize the need for increased research on the diverse presentations of ASD in females and co-occurring conditions to improve diagnostic accuracy.

Question 2

The second research question aimed to measure the probability that individuals from specific demographic groups would receive a diagnosis from a school-based team compared to a physician, clinical psychologist, multidisciplinary team, or healthcare provider. A logistic regression model was used to model the probability of receiving a school-based diagnosis, with the focal predictors including ADI state decile, age (grouped into bands), diagnostic year, family history status, cognitive impairment status, severity, BIPOC status, female status, and their interactions. The final model, with all predictors, is summarized here, as it had the best model fit compared to the two previous models.

ADI state decile significantly predicted the probability of receiving a school-based diagnosis for the fifth and seventh deciles. Individuals in the fifth decile were more likely to receive a school-based diagnosis, whereas individuals in the seventh decile were less likely to receive a school-based diagnosis. The variability in coefficient estimates suggests resource availability is not systematically predicting with the type of provider making the diagnosis.

Specific age bands were also significant predictors of receiving a school-based diagnosis. Preschool-aged (age band two) and elementary-aged (age band three) children were more likely to receive a school-based diagnosis. Middle school aged- and older adolescents (age band four) were not significantly associated with provider type. This is consistent with the practical expectations that initial eligibility and identification would occur in preschool and elementary

school, per IDEA (2004). Diagnostic year was also a significant predictor of the probability of receiving a school-based diagnosis, with each year after the COVID-19 pandemic being associated with a lower probability of receiving a school-based diagnosis. This finding aligns with existing literature, which suggests that the pandemic disrupted school-based evaluations and access to educational assessments (Latzer et al., 2021).

The interaction between age and diagnosis year was significant for age band two (preschool-aged children) and age band four (middle school to high school students) in predicting the probability of receiving a school-based diagnosis. Specifically, preschool-aged children (age band two) were less likely to be identified by a school-based team following the COVID-19 pandemic, beyond the main effects. This suggests that the pandemic may have had a significant impact on families' access to timely resources, leading to delays in evaluations and diagnoses within school districts. Interestingly, children in age band four (middle school to high school) became more likely to receive a school-based diagnosis after the COVID-19 pandemic. This shift may reflect an increase in social difficulties that exacerbated autism spectrum disorder (ASD) symptoms, or it may indicate that these children, possibly lacking adequate healthcare or support resources, relied more heavily on the school system for identification and access to services. Furthermore, the COVID-19 pandemic had a profound effect on child and adolescent mental health, given school closures and the associated reduction in social interactions (Hawrilenko et al., 2021; Viner et al., 2022). It is also possible that the social isolation that occurred during the quarantine period during the pandemic contributed to behaviors resembling ASD. Alternatively, after the pandemic, it is possible that healthcare clinicians prioritized younger children in their diagnostic practices to follow evidence-based practices (e.g., making them less likely to receive a school-based diagnosis), which, in turn, pushed adolescents to

depend more on school-based evaluations due to a lack of resources. Future research should measure this shift, its causes, and the implications for diagnostic access.

Finally, symptom severity and female status negatively predicted the probability of receiving a school-based diagnosis. Specifically, higher symptom severity in females were associated with a lower probability of receiving a school-based diagnosis compared to males with similar severity levels. This may be due to screening practices within medical settings, where screeners are more likely to detect higher symptom severity, even in females, leading to earlier and more accurate diagnoses (Oosterling et al., 2010)). This would reduce the need for a school-based diagnosis, as these children may have already been diagnosed by pediatricians or other healthcare providers.

Limitations

The present study is not without limitations. First, the data is based on parent and caregiver report, leading to recall bias. Retrospective reporting is prone to memory errors, leading to invalid data. Although the SPARK study team employs strategies to flag individual cases for validity issues, participant-reported data is inherently susceptible to errors. Additionally, while SPARK data is nationally recruited, its generalizability is limited. Diagnostic practices, particularly within schools, vary significantly based on available resources and local policies (Safer-Lichtenstein et al., 2020). A major limitation of this study is the unavailability of site location, provider affiliation, or clinician ID (e.g., who provided the diagnosis). This prevents the model from accounting for potential variations in diagnostic age across different locations, leading to violations of statistical assumptions of independence of groups.

Another limitation concerns the interpretation of statistical results due to the large sample size. While a large sample is statistically ideal, the present sample may have artificially inflated

p-values. This could lead to Type 1 error, as the overinflation of p-values may have contributed to statistically significant differences that may not be clinically meaningful or valid. In Question 1, this issue is further supported by the effect sizes in the first model, all of which were .000, suggesting that the observed effects were exceedingly small. Meaning, while several predictors significantly contributed unique variance to the outcome in the model, these contributions were minimal. It is likely that the categorical nature of the variables does not fully capture the complexities of diagnostic timing and school-based practices in the population.

Furthermore, confounding variables such as site membership or clinician ID were not included in the statistical models for the research questions. These variables may account for additional variance in diagnosis age and probability of school-based diagnosis that was not included in the model. This could also account for the observed small effect sizes and unmeasured residual variation, potentially violating statistical assumptions, which, in turn, leads to interpretation errors about the relationships between the predictor and outcome variables.

Similarly, while the overall models in Questions 1 and 2 were statistically significant, their overall model fit for each model was limited. Specifically, for question 1, effect sizes were small, and the R2-changes between models were minimal (with only a 3.1% increase). This suggests that the inclusion of interaction variables, while significant, did not meaningfully improve the overall model. This suggests that while the model became more sensitive to identifying true positives, it also misclassified a large proportion of true negatives, thereby limiting its ability to accurately discriminate between cases. The overall hit rate remained stable at 69.4%, indicating that the model's predictive accuracy did not substantially improve despite the inclusion of interaction terms. These findings highlight a potential limitation in the sensitivity and specificity rates in our models, which should be carefully considered when interpreting the

results. Future studies may need to prioritize optimizing both sensitivity and specificity to improve the model's utility in practical applications.

Furthermore, the study's sample has representation and validity limitations due to language restrictions. Only participants who were fluent in English were included in the original SPARK study, which significantly narrows the sample and limits its diversity. As a result, non-native English speakers, including many individuals from BIPOC and non-Caucasian communities, were excluded. This exclusion skews the sample toward English-speaking individuals, limiting the study's applicability to more diverse populations.

Finally, an important limitation pertains to the distinction between school-based identification of autism and a formal medical diagnosis. State, district, and school policies vary widely regarding whether they diagnose or identify autism independently or require a pre-existing medical diagnosis. While this inconsistency is not aligned with IDEA federal guidelines, many school providers hesitate to diagnose autism due to concerns about their training and expertise. Additionally, special education evaluations in school settings are primarily conducted to determine eligibility for services rather than to provide a formal medical diagnosis. Therefore, school-based identification differs fundamentally from medical diagnoses provided by healthcare professionals.

Implications for Practice

The present study has many implications for future practices. Regarding Question One, it is encouraging that diagnostic practices have shifted toward more timely diagnoses of autism spectrum disorder (ASD) in individuals from BIPOC communities. However, the interactions between severity, cognitive impairment, and later diagnoses indicate a continued fundamental misunderstanding of ASD presentations and co-occurring conditions in BIPOC populations. Future research should focus on outlining these presentations and differential diagnoses using a

culturally sensitive and responsive lens, as well as improving culturally responsive evaluation practices in diverse communities. Similarly, females continue to be diagnosed later, on average, compared to males. This delay is likely due to the different symptomology in females compared to males. The interaction between cognitive impairment and delayed diagnosis in females suggests potential misclassification or misdiagnosis, possibly stemming from a fundamental misunderstanding of autism and its co-occurring conditions within the female population. This finding highlights the need for more nuanced diagnostic frameworks that account for the distinct ways in which autism presents in females, particularly in the presence of cognitive impairments.

Regarding Question Two, there are many implications for clinical and research practices related to school-based autism diagnoses. Notably, the COVID-19 pandemic significantly impacted certain populations in receiving school-based diagnoses. This suggests that schools are still adjusting to a post-pandemic reality, likely due to increased mental health concerns resulting from social isolation and the backlog of children requiring evaluation and services.

Additionally, schools serve as a primary diagnostic resource for BIPOC communities, highlighting their potential role in improving early ASD identification. Schools should increase their diagnostic and identification efforts by prioritizing training on recognizing ASD presentations in BIPOC populations. This need extends to female students, who are less likely to be identified by school-based teams. Increasing awareness and training on female ASD presentations could improve early identification, access to services, and social support opportunities provided by schools.

One potential initiative to address these disparities is multidisciplinary collaboration between schools, community centers, and healthcare providers. Such collaboration could streamline diagnoses, ensure timely and affordable evaluations, and promote culturally

responsive, and gender-sensitive diagnostic practices. Furthermore, integrating diagnostic efforts with community-based treatment providers could help facilitate smoother transitions from diagnosis to intervention. A collaborative treatment system utilized in schools, homes, and clinics, where professionals use similar therapeutic approaches and language, and would benefit children, families, and diagnosticians.

Clinically, while the statistical differences observed in this study were significant, the overall age of diagnosis remains later than what is outlined in best practice (18 months, Baird et al., 2000). Given that ASD can be identified as early as 12 months, but more reliably at 18 months, there continues to be a nearly three-year delay between the earliest diagnosable age and when children are formally diagnosed. Pediatric guidelines recommend ASD screenings beginning at 18 months to ensure early intervention (Baird et al., 2000), as early intervention has been shown to have optimal long-term outcomes (Rogers et al., 2000). However, due to resource shortages and extensive waitlists, which were exacerbated by the COVID-19 pandemic, many families continue to experience significant delays in diagnosis. This highlights the urgent need for improved screening and diagnostic practices. Provider uncertainty in their diagnostic skills also contribute to delays. Accordingly, specific training for ASD identification should be implemented in professional and graduate school psychology programs to ensure school psychologists feel confident in identifying ASD.

ASD prevalence continues to rise, yet diagnostic resources continue to be limited, and the average age of diagnosis has not improved. Thus, increasing education and training on ASD diagnosis within the community is critical. This includes specific training on culturally responsive diagnostic practices for BIPOC communities and increasing awareness of ASD presentations in females. Current diagnostic criteria continue to be centered around White male

presentations of autism, making it essential to implement differential diagnosis approaches that account for cultural and gender-based variability.

Additionally, a stronger referral system could streamline diagnostic processes and improve triage practices for interdisciplinary evaluations. Community physicians, hospitals, and school districts should collaborate to ensure equitable access to ASD evaluations for underserved populations. Given that BIPOC and low-income families rely heavily on school-based diagnostic resources, it is particularly critical that schools and healthcare providers work together to improve accessibility to ASD evaluations in these communities.

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Table 1

Descriptive Statistics for Variables used in Analyses

Variable	*M*	*(SD)*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
Outcomes																			
1. ASD Diagnosis Age (Months)	51.87	(31.04)	--																
2. School-Based ASD Diagnosis (1 = Yes)	0.31	(0.46)	**.04**	--															
Predictors																			
3. ADI State Decile 1 (1 = Yes)	0.25	(0.43)	.00	**-.01**	--														
4. ADI State Decile 2 (1 = Yes)	0.27	(0.44)	**-.01**	**.01**	**-.13**	--													
5. ADI State Decile 3 (1 = Yes)	0.18	(0.38)	.00	.00	**-.12**	**-.13**	--												
6. ADI State Decile 4 (1 = Yes)	0.08	(0.26)	.00	.00	**-.12**	**-.13**	**-.12**	--											
7. ADI State Decile 5 (1 = Yes)	0.17	(0.37)	.00	.00	**-.15**	**-.17**	**-.16**	**-.15**	--										
8. ADI State Decile 6 (1 = Yes)	0.09	(0.29)	**-.01**	.00	**-.11**	**-.12**	**-.11**	**-.11**	**-.14**	--									
9. ADI State Decile 7 (1 = Yes)	0.09	(0.28)	**.01**	**-.02**	**-.10**	**-.12**	**-.11**	**-.11**	**-.14**	**-.10**	--								
10. ADI State Decile 8 (1 = Yes)	0.08	(0.27)	.00	**.01**	**-.10**	**-.11**	**-.11**	**-.10**	**-.13**	**-.10**	**-.09**	--							
11. ADI State Decile 9 (1 = Yes)	0.07	(0.26)	**.01**	.00	**-.10**	**-.11**	**-.10**	**-.10**	**-.13**	**-.09**	**-.09**	**-.09**	--						
12. ADI State Decile 10 (1 = Yes)	0.06	(0.23)	.00	**.01**	**-.08**	**-.09**	**-.09**	**-.09**	**-.11**	**-.08**	**-.08**	**-.07**	**-.07**	--					
13. Diagnosis Year (Center 2019)	-2.05	(2.51)	**.03**	**-.16**	**-.02**	**-.03**	**-.01**	**-.01**	**.13**	**-.03**	**-.01**	**-.02**	**-.02**	**-.01**	--				
15. Family ASD Hist Status (1 = Yes)	0.49	(0.50)	**.03**	**.01**	**-.03**	**-.03**	**-.01**	**.02**	**.01**	.00	.00	**.01**	**.02**	**.03**	.00	--			
14. Indiv Cog Imp Status (1 = Yes)	0.12	(0.33)	**.07**	**.03**	**-.03**	**-.02**	**-.02**	**-.01**	**.01**	**.01**	**.01**	**.02**	**.01**	**.02**	**-.06**	**.01**	--		
16. Indiv SCQ Severity (Points)	22.09	(5.99)	**-.07**	**.05**	**-.07**	**-.06**	**-.02**	**-.01**	**.02**	**.02**	**.03**	**.04**	**.03**	**.04**	**-.10**	**.05**	**.13**	--	
17. Indiv BIPOC Status (1 = Yes)	0.38	(0.49)	**-.11**	**.05**	**-.02**	**-.02**	**-.02**	**-.01**	**.00**	**.01**	**.02**	**.01**	**.02**	**.04**	**.03**	**-.01**	**.01**	**.01**	--
18. Indiv Female Status (1 = Yes)	0.21	(0.41)	**.03**	**-.03**	**-.01**	**-.02**	**-.01**	.00	**.02**	**.01**	**-.01**	.00	.00	.00	**.05**	**.03**	**.04**	**-.01**	.00

Note. N = 18,518 probands from SPARK study collected from 2013-2023. Variables with names ending in Status or Decile are dummy-coded (1 = Yes, 0 = No). Categorical predictor dummy-coded variables are coded so means represent the percentage of individuals in each category. School-Team Diagnosis is dummy coded, with 1 = diagnosis provided by a school-based team and 0 = else. ADI State = Area Deprivation Index are coded in deciles at the state level. SCQ Severity = Raw score from the Social Communication Questionnaire. BIPOC Status = Black, Indigenous, and People of Color. Pearson's r reported. Boldfaced correlations are those that are statistically significant from zero ($p < .05$, 2-tailed).

Table 2

Multiple Linear Regression Model Results Predicting Log(Age) of ASD Diagnosis

Coefficient	Model 1 (Baseline)					Model 2 (Focal Factors)					Model 3 (Interactions)				
	Est	*(SE)*	*t*	*p*	sr^2	*Est*	*(SE)*	*t*	*p*	sr^2	*Est*	*(SE)*	*t*	*p*	sr^2
Intercept (Conditional Mean)	**3.80**	**(0.00)**	**939.25**	**<.001**		**3.85**	**(0.01)**	**519.00**	**<.001**		**3.87**	**(0.01)**	**419.35**	**<.001**	
ADI State Decile 2 (1= Yes)	**-0.02**	**(0.01)**	**-2.05**	**.041**	**.000**	**-0.03**	**(0.01)**	**-2.63**	**.009**	**.000**	**-0.03**	**(0.01)**	**-2.75**	**.006**	**.000**
ADI State Decile 3 (1= Yes)	0.00	(0.01)	-0.12	.902	.000	-0.01	(0.01)	-0.54	.587	.000	-0.01	(0.01)	-0.65	.515	.000
ADI State Decile 4 (1= Yes)	0.01	(0.01)	0.46	.644	.000	0.00	(0.01)	0.11	.913	.000	0.00	(0.01)	0.00	.997	.000
ADI State Decile 5 (1= Yes)	-0.01	(0.01)	-0.76	.445	.000	-0.01	(0.01)	-1.10	.270	.000	-0.01	(0.01)	-1.01	.314	.000
ADI State Decile 6 (1= Yes)	-0.01	(0.01)	-0.92	.357	.000	-0.01	(0.01)	-0.70	.486	.000	-0.01	(0.01)	-0.71	.477	.000
ADI State Decile 7 (1= Yes)	0.02	(0.01)	1.17	.244	.000	0.02	(0.01)	1.60	.109	.000	0.02	(0.01)	1.61	.107	.000
ADI State Decile 8 (1= Yes)	0.01	(0.01)	0.71	.480	.000	0.01	(0.01)	1.05	.296	.000	0.01	(0.01)	1.11	.268	.000
ADI State Decile 9 (1= Yes)	0.02	(0.01)	1.66	.097	.000	**0.03**	**(0.01)**	**2.07**	**.039**	**.000**	**0.03**	**(0.01)**	**2.19**	**.028**	**.000**
ADI State Decile 10 (1= Yes)	0.00	(0.02)	-0.16	.872	.000	0.01	(0.02)	0.50	.616	.000	0.01	(0.02)	0.63	.532	.000
Diag Year (center 2019) (DxYear)						0.00	(0.00)	1.72	.086	.000	**0.01**	**(0.00)**	**4.56**	**<.001**	**.001**
Fam ASD Hist (1= Yes) (FamilyHx)						**0.01**	**(0.00)**	**3.47**	**.001**	**.001**	0.00	(0.01)	0.14	.886	.000
Indiv Cog Imp (1 = Yes) (CogImp)						**0.07**	**(0.01)**	**11.15**	**<.001**	**.007**	**0.10**	**(0.01)**	**11.21**	**<.001**	**.007**
Indiv SCQ Severity (Z) (ZSCQ)						**-0.04**	**(0.00)**	**-10.56**	**<.001**	**.006**	**-0.05**	**(0.01)**	**-7.31**	**<.001**	**.003**
Indiv BIPOC (1 = Yes) (BIPOC)						**-0.06**	**(0.00)**	**-15.34**	**<.001**	**.012**	**-0.05**	**(0.01)**	**-7.02**	**<.001**	**.003**
Indiv Female (1 = Yes) (Female)						0.01	(0.01)	1.28	.200	.000	**0.02**	**(0.01)**	**2.24**	**.025**	**.000**
DxYear*FamilyHx											0.00	(0.00)	0.51	.608	.000
DxYear*CogImp											**0.01**	**(0.00)**	**4.61**	**<.001**	**.001**
DxYear*ZSCQ											**-0.01**	**(0.00)**	**-5.57**	**<.001**	**.002**
DxYear*BIPOC											0.00	(0.00)	-0.38	.705	.000
DxYear*Female											0.00	(0.00)	0.63	.532	.000

(cont'd next page)

Table 2, Continued

Multiple Linear Regression Model Results Predicting Log(Age) of ASD Diagnosis

Coefficient	Model 1 (Baseline)					Model 2 (Focal Factors)					Model 3 (Interactions)				
	Est	*(SE)*	*t*	*p*	sr^2	*Est*	*(SE)*	*t*	*p*	sr^2	*Est*	*(SE)*	*t*	*p*	sr^2
FamilyHx*CogImp											**-0.02**	**(0.01)**	**-3.71**	**<.001**	**.001**
FamilyHx*ZSCQ											0.00	(0.00)	1.07	.284	.000
FamilyHx*BIPOC											0.00	(0.00)	-0.52	.601	.000
FamilyHx*Female											0.01	(0.01)	1.38	.169	.000
CogImp*ZSCQ											0.01	(0.01)	1.42	.156	.000
CogImp*BIPOC											**0.02**	**(0.01)**	**2.39**	**.017**	**.000**
CogImp*Female											**0.01**	**(0.01)**	**2.03**	**.042**	**.000**
ZSCQ*BIPOC											**0.02**	**(0.00)**	**5.17**	**<.001**	**.001**
ZSCQ*Female											**-0.01**	**(0.01)**	**-2.22**	**.026**	**.000**
BIPOC*Female											0.00	(0.01)	-0.31	.756	.000

Note. N = 18,518 probands from the SPARK study collected from 2013-2023. Linear sequential regression in R used to model results with alpha = .05, 2-tailed. Statistical significance ($p < .05$) indicated in boldface. All categorical predictors are effect-coded (ADI State Decile 1 category served as the reference category for ADI State Decile groupings). All continuous predictors are standardized as *z*-scores. Effect size sr^2 is the squared semi-partial correlation, which indicates the unique variance in outcome explained by the predictor.

Table 3

Multiple Logistic Regression Model Results Predicting Likelihood of ASD Diagnosis by School-Based Team

Coefficient	Model 1 (Baseline)						Model 2 (Focal Factors)						Model 3 (Interactions)					
					95% CI						95% CI						*OR* 95% CI	
	Est	*(SE)*	*p*	*OR*	[LB,	UB]	*Est*	*(SE)*	*p*	*OR*	[LB,	UB]	*Est*	*(SE)*	*p*	*OR*	[LB,	UB]
Intercept (Mean)	**-0.82**	**(0.02)**	**<.001**	**0.44**	**[0.43 ,**	**0.46]**	**-1.14**	**(0.04)**	**<.001**	**0.32**	**[0.29 ,**	**0.35]**	**-1.10**	**(0.06)**	**<.001**	**0.33**	**[0.30 ,**	**0.37]**
ADI State Decile 2 (1= Yes)	0.04	(0.04)	.423	1.04	[0.95 ,	1.13]	0.05	(0.05)	.291	1.05	[0.96 ,	1.14]	0.04	(0.05)	.336	1.04	[0.96 ,	1.14]
ADI State Decile 3 (1= Yes)	-0.02	(0.05)	.605	0.98	[0.89 ,	1.07]	-0.01	(0.05)	.898	0.99	[0.91 ,	1.09]	-0.01	(0.05)	.847	0.99	[0.90 ,	1.09]
ADI State Decile 4 (1= Yes)	0.00	(0.05)	.977	1.00	[0.91 ,	1.09]	0.00	(0.05)	.976	1.00	[0.91 ,	1.10]	0.00	(0.05)	.944	1.00	[0.91 ,	1.10]
ADI State Decile 5 (1= Yes)	0.00	(0.04)	.956	1.00	[0.93 ,	1.08]	**0.11**	**(0.04)**	**.005**	**1.12**	**[1.03 ,**	**1.21]**	**0.11**	**(0.04)**	**.005**	**1.12**	**[1.04 ,**	**1.21]**
ADI State Decile 6 (1= Yes)	-0.03	(0.05)	.563	0.97	[0.88 ,	1.07]	-0.05	(0.05)	.309	0.95	[0.86 ,	1.05]	-0.06	(0.05)	.246	0.94	[0.85 ,	1.04]
ADI State Decile 7 (1= Yes)	**-0.12**	**(0.05)**	**.022**	**0.89**	**[0.80 ,**	**0.98]**	**-0.14**	**(0.05)**	**.007**	**0.87**	**[0.78 ,**	**0.96]**	**-0.14**	**(0.05)**	**.008**	**0.87**	**[0.78 ,**	**0.96]**
ADI State Decile 8 (1= Yes)	0.07	(0.05)	.171	1.07	[0.97 ,	1.19]	0.04	(0.05)	.445	1.04	[0.94 ,	1.16]	0.04	(0.05)	.419	1.04	[0.94 ,	1.16]
ADI State Decile 9 (1= Yes)	0.03	(0.06)	.611	1.03	[0.92 ,	1.14]	-0.01	(0.06)	.839	0.99	[0.89 ,	1.10]	-0.01	(0.06)	.890	0.99	[0.89 ,	1.11]
ADI State Decile 10 (1= Yes)	0.07	(0.06)	.256	1.07	[0.95 ,	1.21]	0.03	(0.06)	.607	1.03	[0.91 ,	1.17]	0.04	(0.06)	.570	1.04	[0.92 ,	1.17]
Age-Band 2 (3-4.9 years)							**0.14**	**(0.04)**	**.001**	**1.15**	**[1.06 ,**	**1.24]**	**0.14**	**(0.07)**	**.039**	**1.15**	**[1.01 ,**	**1.31]**
Age-Band 3 (5-11.9 years)							**0.20**	**(0.04)**	**<.001**	**1.22**	**[1.13 ,**	**1.33]**	**0.28**	**(0.07)**	**<.001**	**1.32**	**[1.16 ,**	**1.51]**
Age-Band 4 (12-17.9 years)							-0.05	(0.10)	.637	0.95	[0.78 ,	1.16]	-0.01	(0.14)	.929	0.99	[0.74 ,	1.30]
Diag Year (center 2019) (DxYear)							**-0.14**	**(0.01)**	**<.001**	**0.87**	**[0.86 ,**	**0.88]**	**-0.09**	**(0.02)**	**<.001**	**0.92**	**[0.88 ,**	**0.95]**
Fam ASD Hist (1= Yes) (FamilyHx)							0.02	(0.02)	.201	1.02	[0.99 ,	1.05]	0.07	(0.04)	.102	1.07	[0.99 ,	1.17]
Indiv Cog Imp (1 = Yes) (CogImp)							0.02	(0.03)	.342	1.02	[0.98 ,	1.07]	0.08	(0.05)	.128	1.08	[0.98 ,	1.20]
Indiv SCQ Severity (Z) (ZSCQ)							**0.07**	**(0.02)**	**<.001**	**1.08**	**[1.04 ,**	**1.11]**	0.08	(0.04)	.051	1.09	[1.00 ,	1.18]
Indiv BIPOC (1 = Yes) (BIPOC)							**0.15**	**(0.02)**	**<.001**	**1.16**	**[1.12 ,**	**1.20]**	**0.19**	**(0.05)**	**<.001**	**1.21**	**[1.11 ,**	**1.32]**
Indiv Female (1 = Yes) (Female)							**-0.07**	**(0.02)**	**.001**	**0.93**	**[0.90 ,**	**0.97]**	**-0.11**	**(0.05)**	**.032**	**0.90**	**[0.82 ,**	**0.99]**
AgeBand2*DxYear													**-0.04**	**(0.02)**	**.050**	**0.97**	**[0.93 ,**	**1.00]**
AgeBand2*FamilyHx													-0.02	(0.04)	.572	0.98	[0.90 ,	1.06]
AgeBand2*CogImp													-0.07	(0.06)	.216	0.94	[0.84 ,	1.04]
AgeBand2*ZSCQSeverity													-0.01	(0.04)	.794	0.99	[0.92 ,	1.07]
AgeBand2*BIPOC													0.03	(0.04)	.549	1.03	[0.94 ,	1.12]
AgeBand2*Female													0.09	(0.05)	.061	1.10	[1.00 ,	1.21]

(cont'd next page)

Table 3, Continued

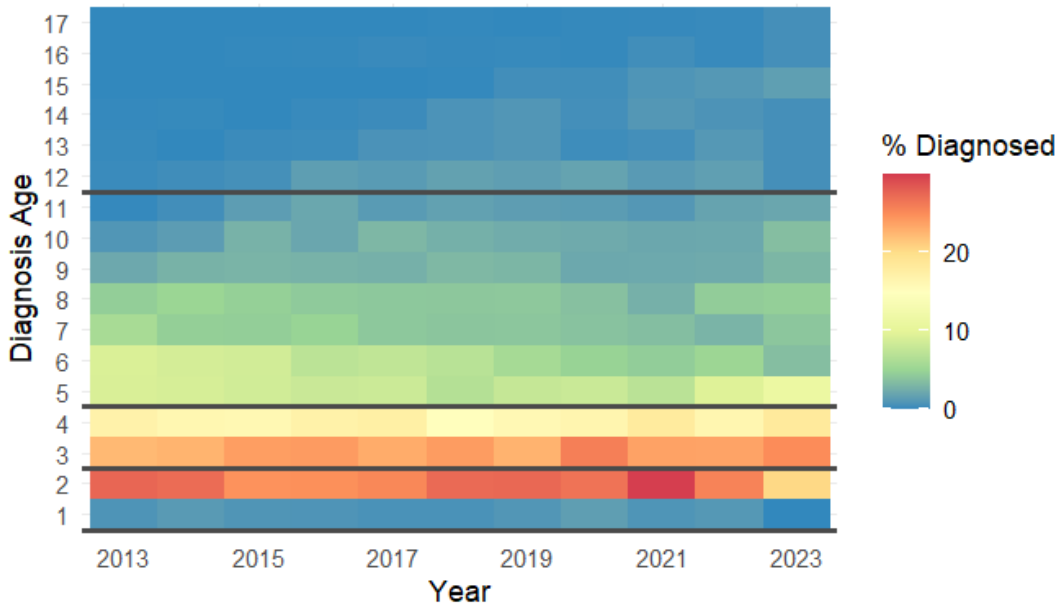
Multiple Logistic Regression Model Results Predicting Likelihood of ASD Diagnosis by School-Based Team

Coefficient	Model 1					Model 2					Model 3				
					95% CI					95% CI					*OR* 95% CI
	Est	*(SE)*	*p*	*OR*	[LB, UB]	*Est*	*(SE)*	*p*	*OR*	[LB, UB]	*Est*	*(SE)*	*p*	*OR*	[LB, UB]
AgeBand3*DxYear											0.02	(0.02)	.285	1.02	[0.98 , 1.06]
AgeBand3*FamilyHx											-0.02	(0.04)	.645	0.98	[0.90 , 1.06]
AgeBand3*CogImp											-0.06	(0.05)	.271	0.94	[0.85 , 1.05]
AgeBand3*ZSCQSeverity											-0.02	(0.04)	.713	0.99	[0.91 , 1.07]
AgeBand3*BIPOC											-0.05	(0.04)	.236	0.95	[0.87 , 1.04]
AgeBand3*Female											0.02	(0.05)	.711	1.02	[0.93 , 1.13]
AgeBand4*DxYear											**0.13**	**(0.05)**	**.003**	**1.14**	**[1.05 , 1.25]**
AgeBand4*FamilyHx											0.01	(0.10)	.941	1.01	[0.83 , 1.23]
AgeBand4*CogImp											0.04	(0.13)	.734	1.04	[0.81 , 1.33]
AgeBand4*ZSCQSeverity											0.03	(0.10)	.799	1.03	[0.85 , 1.24]
AgeBand4*BIPOC											0.00	(0.11)	.990	1.00	[0.81 , 1.23]
AgeBand4*Female											-0.16	(0.12)	.184	0.85	[0.67 , 1.07]
DxYear*FamilyHx											0.00	(0.01)	.611	1.00	[0.99 , 1.02]
DxYear*CogImp											0.02	(0.01)	.142	1.02	[1.00 , 1.04]
DxYear*ZSCQ											0.00	(0.01)	.857	1.00	[0.99 , 1.01]
DxYear*BIPOC											0.01	(0.01)	.440	1.01	[0.99 , 1.02]
DxYear*Female											0.00	(0.01)	.764	1.00	[0.98 , 1.01]
FamilyHx*CogImp											0.05	(0.03)	.051	1.05	[1.00 , 1.10]
FamilyHx*ZSCQ											0.02	(0.02)	.312	1.02	[0.98 , 1.05]
FamilyHx*BIPOC											0.02	(0.02)	.211	1.02	[0.99 , 1.06]
FamilyHx*Female											0.00	(0.02)	.903	1.00	[0.96 , 1.04]
CogImp*ZSCQ											0.05	(0.03)	.051	1.05	[1.00 , 1.10]
CogImp*BIPOC											0.03	(0.03)	.227	1.03	[0.98 , 1.08]
CogImp*Female											0.02	(0.03)	.478	1.02	[0.96 , 1.08]
ZSCQ*BIPOC											-0.01	(0.02)	.400	0.99	[0.95 , 1.02]
ZSCQ*Female											**-0.06**	**(0.02)**	**.005**	**0.94**	**[0.91 , 0.98]**
BIPOC*Female											0.02	(0.02)	.483	1.02	[0.97 , 1.06]

Note. N = 18,518 probands from SPARK study collected from 2013-2023. Results reported in logits. Maximum likelihood logistic regression in *R* used to model results, with alpha = .05, 2-tailed. Statistical significance ($p < .05$) indicated in boldface. All categorical predictors effect-coded (ADIstate Decile 1 category and Age-Band 1 category served as the reference category for their groupings). All continuous predictors standardized as z-scores. *OR* = Odds Ratio.

Figure 1

Heat Map of ASD Diagnosis Age by Year of Study



Note. N = 18,518 probands from SPARK study collected from 2013-2023. Age bands are shown with horizontal black lines.

Figure 2

Model-Predicted ASD Diagnosis Age by ASD Severity and Female Status.

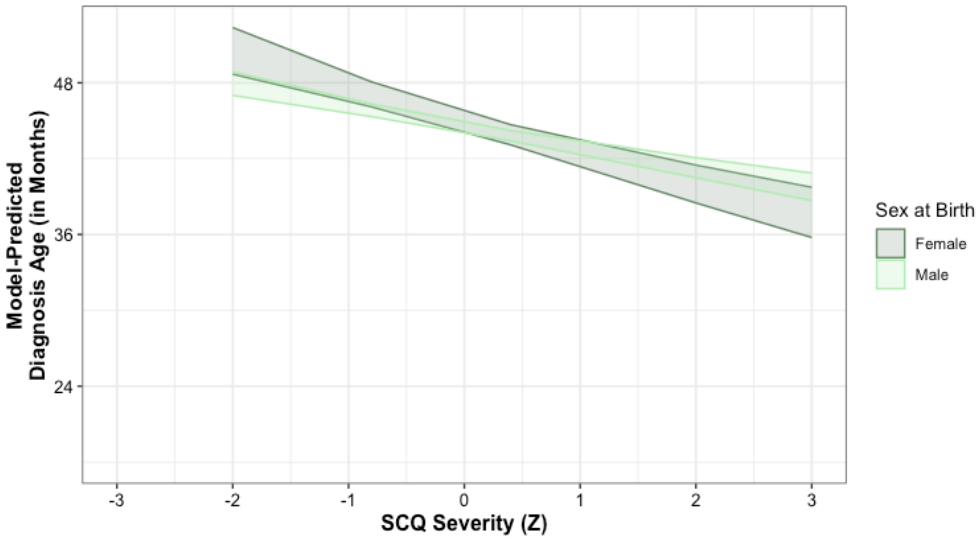


Figure 3

Model-Predicted ASD Diagnosis by ASD Severity and BIPOC Status

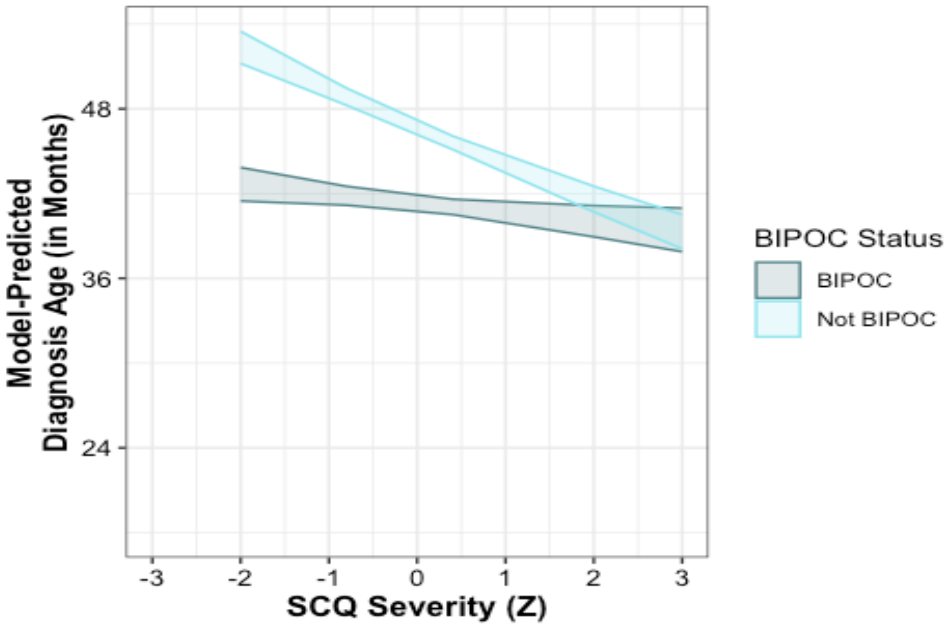
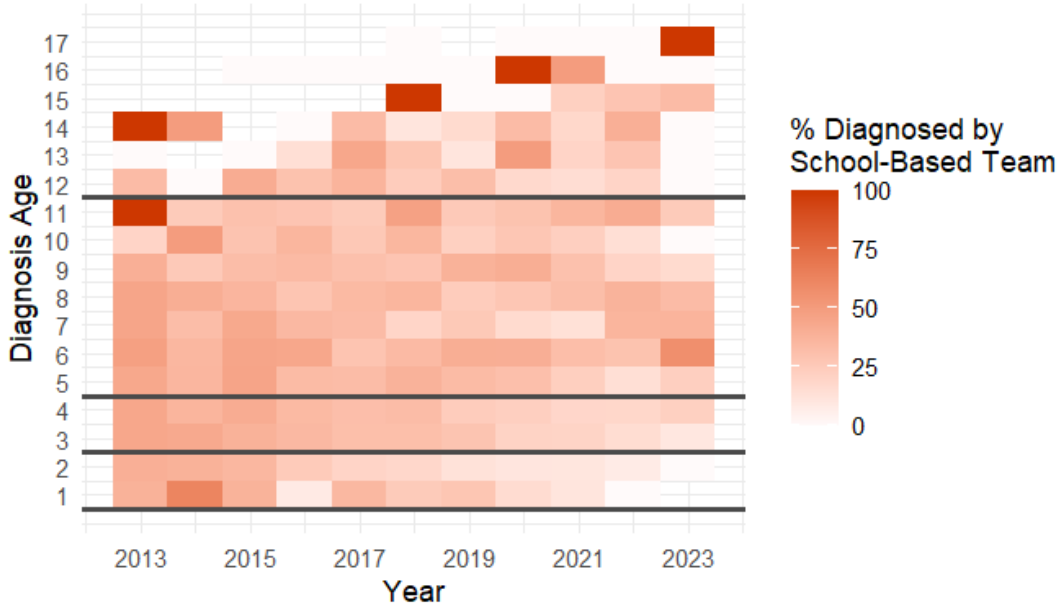


Figure 4

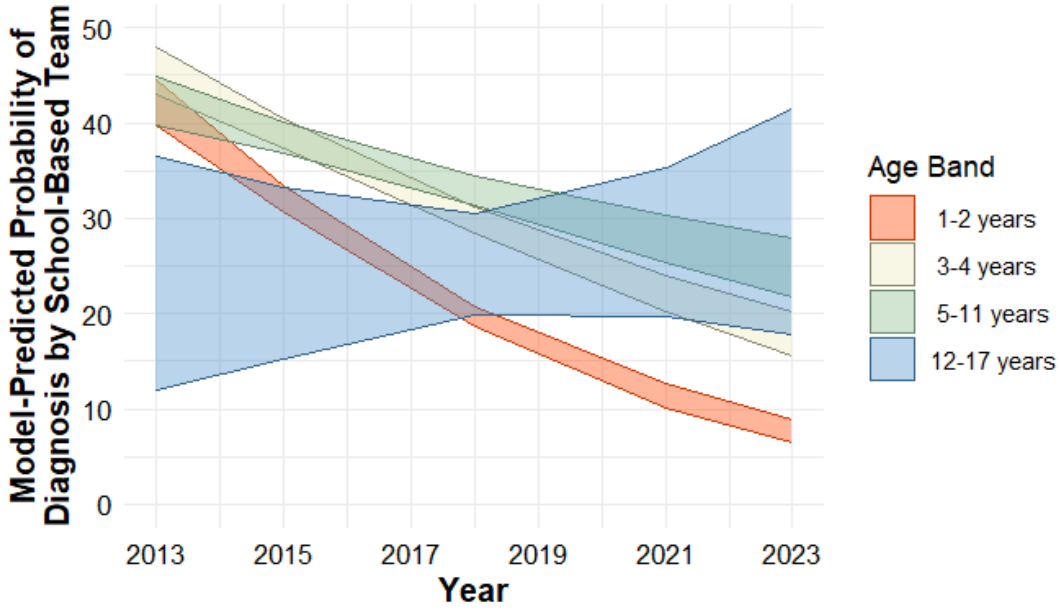
Heat Map of ASD Diagnosis by a School-Based Team, by Diagnosis Age and Year of Study



Note. N = 18,518 probands from SPARK study collected from 2013-2023. Age bands are shown with horizontal black lines.

Figure 5

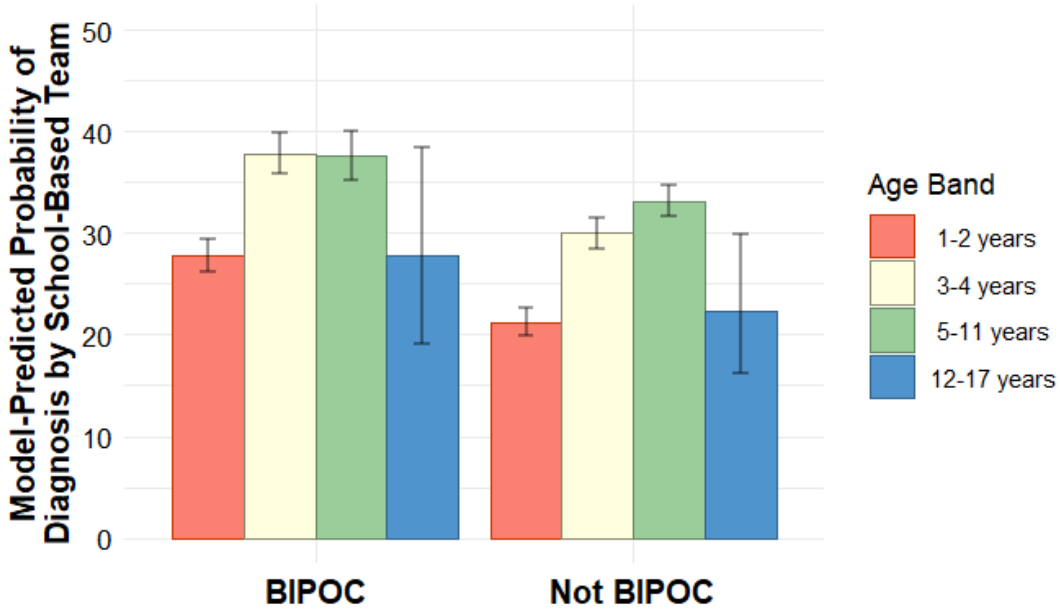
Model-Predicted Probability of ASD Diagnosis by a School-Based Team by Year and Age



Note. N = 18,518 probands from SPARK study collected from 2013-2023. Shaded regions = 95% confidence intervals.

Figure 6

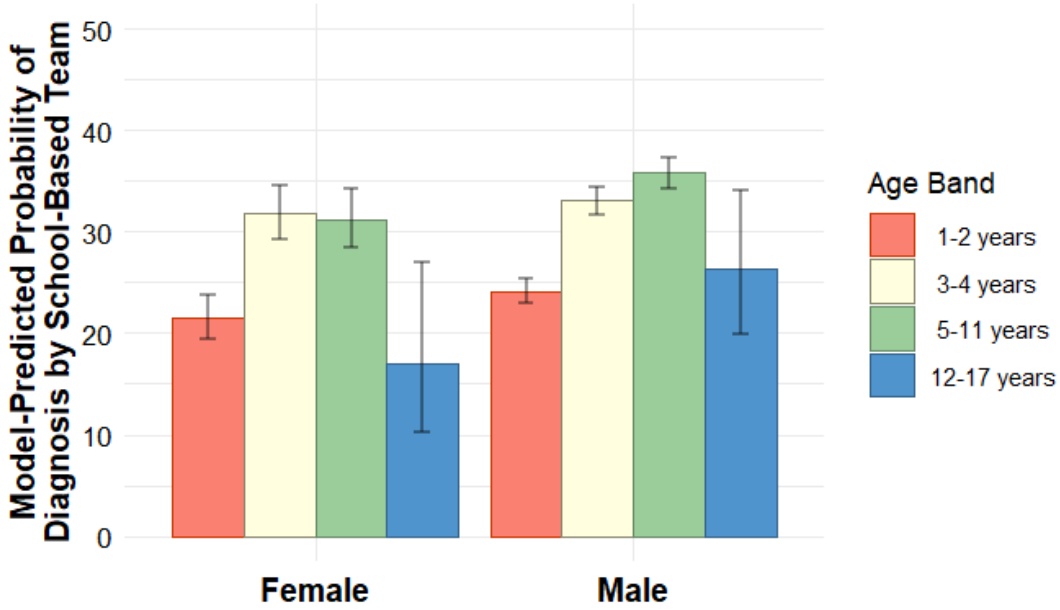
Model-Predicted Probability of ASD Diagnosis by School-Based Team by BIPOC Status and Age



Note. N = 18,518 probands from SPARK study collected from 2013-2023.

Figure 7

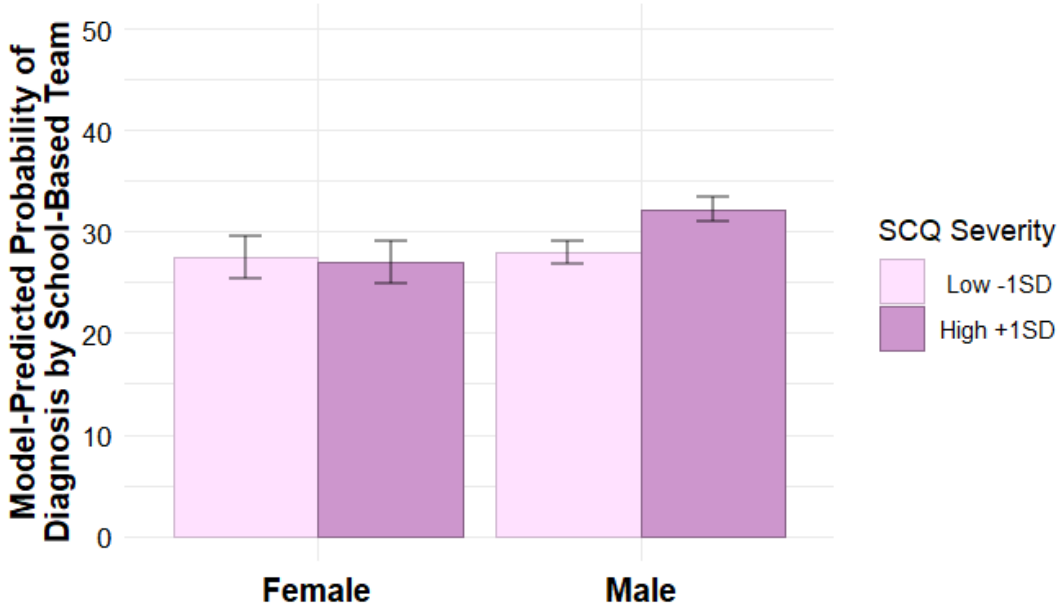
Model-Predicted Probability of ASD Diagnosis by School-Based Team by Sex and Age



Note. N = 18,518 probands from SPARK study collected from 2013-2023.

Figure 8

Model-Predicted Probability of ASD Diagnosis by School-Based Team by Sex and SCQ Severity



Note. N = 18,518 probands from SPARK study collected from 2013-2023.