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THE COGNITIVE VALUE OF SOCIAL RELATIONSHIPS: AN ARGUMENT FOR SOCIAL NETWORK THEORY IN DEVELOPMENTAL SCIENCE

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NICOLE BURKE

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To my fellow dreamers and to the people who tell us “no” – this one is for us. May we always continue to rise.

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ABSTRACT

Psychologists have long been interested in understanding how the early social environment impacts children's behavior, thoughts, and minds. From birth, children are embedded in a world rich with social relationships; however, there have been very few tools with which one could even begin to quantify the depth and breadth of children's early social relationships. In this dissertation, I harness the insights and power of social network analysis to demonstrate that developmental psychologists can use social networks to capture and describe early social environments. Once early social experience is conceptualized as network properties, social network theory can be used as a framework to generate questions about how early social environments relate to social cognitive development.

In Chapter 1, I describe the method I created – *The Child Social Network Questionnaire*. Using descriptive social network data from over 300 American children, I demonstrate that network properties can be used to provide a quantitative analysis of children's early social experience and how that experience varies across development, social group membership, and childcare experiences. In Chapter 2, I test the hypotheses generated from a social network perspective about how network properties – Network Size and Network Language Diversity – relate to 3-year-old's perspective-taking (PT) ability. Results show Network Size is positively related to children's PT skill and exploratory analyses suggest that Network Language Diversity has different effects on social cognitive skill in different sized social networks. In Chapter 3, I use preschooler's network properties to explore how Network Racial Diversity relates to children's racial friendship choices. Across several analyses, I find racial outgroup exposure is not created equal; how it relates to racial preferences depends on the Network Size, Network Structure, and the broader social environment.

Introduction

Developmental psychologists who are interested children's early social cognition have a keen interest in understanding how children's early social experiences shape their behavior, thoughts, and mind. Children are born into a world that is rich with social information – they are a part of varied social groups and cultures and children must learn to navigate these social organizations with different rules and customs. While children certainly learn about the world through their own action (Piaget & Inhelder, 1969), children come to learn about the social world through their social relationships; they gain social cognitive capacities by interacting with their social relationships and they learn about social conventions and rules by interacting and observing their social relationships (Gaskins & Paradise, 2010; Vygotsky, 1978).

Sociocultural theories have been the leading theories to understand how social interactions affect the developing child – these theories emphasize the cultural context in which children learn and develop and how social interaction is the engine of learning and development (Tomasello, 2001, 2009; Vygotsky, 1962, 1978). The focus of these theories is how social interactions shape children's knowledge construction and that social interactions take place in different cultural contexts. There is a particular focus on how children use socio-pragmatic cues to understand language (Booth et al., 2008; Tomasello, 2000) and culture (Rogoff, 2003; Tomasello, 2016). Sociocultural theories highlight how important social interactions are for development. In addition to the focus on the child as a social learner, these theories explore how children's experience can vary across culture.

Sociocultural theories do an excellent job to highlight how variation at the level of culture impacts children's learning. There is growing interest in the field to further explore how variations in children's regular social contact and early social experience impact social cognitive development (see Fan et al., 2015 for an example); however, this dimension of early social experience – the people a child has regular social contact with – has largely been ignored in prior developmental work. In a typical week, young children interact with a range of social partners. Young children engage with their family members in the home, they see neighbors on the weekends, they go to library story hour and see the librarian and other kids, and they might attend daycare or preschool and interact with teachers and fellow classmates. Young children's early social relationships provide data to them about how the social world is structured and how it functions. Observing and interacting with different social relationships likely affects the skills children come to develop in social interaction, as well as inform their early attitudes and thoughts about different social groups.

Although this dimension of early social experience provides rich data to children about the structure and function of their early social world, there are relatively few tools available that can describe the breadth and depth of children's early social relationships. In this dissertation, I argue that social networks are a powerful tool and framework that developmental psychologists can use to inform our study of early social cognition. Psychologists often have research questions that ask about an individual's attitudes, cognition, or behavior, but to understand an individual's cognition or behavior, it is necessary to consider how the individual is embedded in a broader social context. A powerful framework for capturing how the individual is embedded in a broader social context is Social Network Theory. A social network perspective can inform the study of early social cognition in two important ways. First, social networks can capture and describe important aspects of children's early social experience and provide a novel way to explore children's complex and embedded early social environments. Second, a social network framework will generate questions and hypotheses not previously asked to better understand how early social experience affects social cognition.

The complicated answer to "What is a social network?"

Before I outline the benefits to be gained by using a social network perspective, it is important to establish an operational definition of a social network. An operational definition of a social network is no small task because the term "social network" refers to several different literatures with several different meanings; social networks are a powerful, flexible tool that can be used to describe and study network structure across several different disciplines.

Simply put, a network is a set of objects or actors and the connections between them (Perry et al., 2018; Wasserman & Faust, 1994). Social Network Theory is used to study a variety of groups – adults, adolescents, animals – and it is used to ask several different kinds of research questions. A social network perspective can be used to study how sexually transmitted diseases spread throughout a high school (Bearman et al., 2004), how the relationships between hospital employees relate to patient outcomes (Blau, 1995), and it has even been used by biologists to understand structure and patterns of relationships in animals (Croft et al., 2005; Croft et al., 2008; Lusseau et al., 2006).

Social networks come in two different forms – sociocentric and egocentric. Sociocentric networks, or whole networks, study a phenomenon at the level of the social system. The examples highlighted above are sociocentric networks; you could track the romantic relationships in a single high school and study how sexually transmitted diseases spread in that particular high school (Bearman et al., 2004). Egocentric networks are personal social networks – these are networks that capture the people immediately surrounding an individual, or "ego" (Robins, 2015). Psychologists are typically more concerned with egocentric networks – how an individual's social network will impact an individual outcome, such as cognition or behavior. There has been plenty of work with adults and adolescents that have studied these kinds of networks. A social network perspective can be used to ask how the personal social network of an individual affects their mental and physical health (Haines & Hurlbert, 1992; Smith & Christakis, 2008), whether the presence of a smoker in an adolescent's peer network will influence whether they become a smoker (Alexander et al., 2001), or even if social network size is related to brain size in adults (Bickart et al., 2011).

These examples demonstrate that Social Network Theory is powerful and flexible because it can be used to study social phenomenon at several different levels of analysis and across several different populations. Because Social Network Theory can be used to study network structure across several different disciplines there has been an explosion of network research in the past several decades (Borgatti & Halgin, 2011). This explosion of research is seen within the psychological sciences as well, with substantial increases of network research in education (McPherson et al., 2001) and in social psychology (Clifton & Webster, 2017). Network theorists argue that we have seen this explosion of research because networks can be studied at multiple levels and Social Network Theory combines a lot of rich data – both qualitative and quantitative – that make it an excellent tool for studying social phenomenon.

Yet, despite this increase of network research in psychological sciences, very little work has explored the personal social networks of young children. If you put in the search term "social networks" on the APA PsycArticles database from 1990 to early 2021 and search for developmental samples (birth to 12-years-old) there are only 44 articles. Most of the 44 articles are looking at sociocentric social networks or networks that are bounded by the classroom or school. For example, a study wanted to explore whether there was any relationship between peer networks and children's reading skill in 2nd and 3rd grade classrooms (Cooc & Kim, 2017). The network boundaries are the students in the 2nd and 3rd grade classrooms, not everyone each student is connected to outside the classroom. Young children's egocentric social networks have largely been ignored by prior work – we know very little about the composition of these networks or how aspects of networks might influence social cognition.

Historical Perspective

The vacuum of social network research in developmental science is striking given the history of network science. Modern day social network analysis is often attributed to the work of Jacob Moreno during the 1930's. He is the founder of sociometry or the study of social relationships (Moreno, 1934; Freeman, 2004); however, several years before Moreno started writing about the structure of relationships, developmental and educational psychologists were asking their own questions about the structure of children's relationships. During the 1920's, large-scale research grants were awarded to child-welfare institutions at various institutions across the US and the research was focused on children's interpersonal relationships (Freeman, 2004). There were several developmentalists that were asking social network questions before the term "network" even existed[1]. As a result, these scientists innovated network methods themselves. Their methods of data collection and data management predated the procedures usually credited to more traditional network scientists.

For example, John Almack (1922, as cited in Freeman, 2004) developed an interview to collect social network – he asked children to report who they would like to invite to a party – 10 years before Moreno developed a similar method. Beth Wellman (1926) developed a data collection method that involved systematically recording which children played with each other

[1] The term "network" was first coined by Jacob Moreno in the 1930's. He said sociometry was like "geography of psychology" (Freeman, 2004).

during a free play session. Helen Bott (1928, as cited in Freeman, 2004) improved Wellman's method by using matrices to record her network data – it would be another 18 years before network scientists would think to use matrices as a way to represent and analyze network data (Forsyth & Katz, 1946). Finally, Elizabeth Hagman (1933) used both observation and interview to discover that there were discrepancies in who children said their friends were versus who they actually played with in a free play session. This important methodological discovery is still a key focus of network research today. These developmental psychologists were asking novel questions about the structure of children's social worlds, but because their focus of study was on the outcomes of children, rather than the structure of relationships themselves, they are not credited with these important methodological innovations.

The next resurgence of network ideas in developmental science would occur in the late 1970's and 1980's. During this time, several scholars became interested in using social networks to ask whether the networks of parents impacted children. These researchers laid out theoretical arguments that children are heavily influenced by their parents; therefore, it is possible that properties of parent social networks might impact the developing child (Cochran & Brassard, 1979). This work only briefly mentions children's own networks. In a volume reviewing their initial paper 14 years later, Cochran writes, "Only touched upon briefly in the article were the personal networks of the children themselves. These, we felt, could be expected in the preschool years to overlap heavily with the networks of their parents, but would in all probability become increasingly distinct later in childhood and during adolescence" (Cochran et al., 1993, p. 17).

Cochran and Bassard (1979) laid out theoretically interesting arguments about how parent networks might relate to the development of the child; however, as I will argue below, it is limited in scope to not consider the social network of a child themselves. Prior work used network theory to generate hypotheses about how parent social networks might impact children's development; however, it is much more powerful to use network theory to ask questions about how children's own social networks relate to their development.

Using Social Network Theory to generate questions for Social Cognition

In Chapter 1, I will introduce a new method for studying the social networks of young children, *The Child Social Network Questionnaire.* I will present data from 300 American children to demonstrate how network properties can be used to capture and describe children's early social experience. Across several analyses, I demonstrate that several aspects of early social environments vary across developmental time. Most notably, as children get older network size increases. During the first few years of early childhood, the number of regular social contacts children has increases. Results also show that increases in network size entails increases in network diversity as well as network complexity; as networks grow in size, they also increase in the number of varied social partners as well as more complex network structure.

In addition to being an excellent tool to quantify early social environments, a social network perspective is a useful framework for thinking about the kinds of effects network properties could have on children's social cognition. Using a social network perspective raises interesting questions to consider for children's social cognitive development. Social cognition is a broad term, but I define social cognition into two specific branches: social cognitive skills, such as theory of mind or perspective-taking, and intergroup cognition – how children reason about different social groups. Below, I review the relevant developmental literature that has explored how early social experience affects these two branches of social cognitive development.

Social Cognitive Skills

Social cognitive skills, such as perspective-taking, theory of mind, and communication skills, emerge early in development and are essential for social interaction and social learning. A great deal of work has investigated whether and when children express these abilities, and smaller bodies of work have asked how aspects of the social environment, for example the presence of siblings or multilingual experience, may relate to them. Considering social networks raises interesting questions and hypotheses to be tested.

First, does children's social network size relate to their social cognitive skill? It is possible children in larger social networks might have superior social cognitive skills because they have more experience using these skills. Not only do they have more experience with these skills, but they have more experience interacting with people outside their immediate family; this varied kind of social interaction could provide rich gains in social cognitive skill. Prior work with adults and primates suggest this hypothesis might be true for children. Adults with larger social networks are better at perspective-taking (Stiller & Dunbar, 2007) and social network size has been shown to be correlated with the neural substrates of social cognition in both adults (Bickart et al., 2011) and non-human primates (Sallet et al., 2011).

The research exploring the effects of siblings on theory of mind also suggests that network size is an important dimension in early childhood for social cognitive skills. This literature about the effects of the number of siblings provides mixed evidence - while there are several studies that find children with siblings perform better on theory of mind tasks than only-children (e.g., Jenkins & Astington, 1996; McAlister & Peterson, 2007; McAlister & Peterson, 2013; Perner et al., 1994; Ruffman et al., 1998), there are also studies that do not find an effect of siblings on theory of mind (e.g., Arranz et al., 2002; Cutting & Dunn, 1999; Hughes & Ensor, 2005). The literature might be mixed for siblings and theory of mind because the scope used to assess early social experience is too narrow. It is possible it is not the number of siblings that matter, but rather network size. The studies that found the number of school friends was related to theory of mind skill (Shahaeian, 2015; Wright & Mahfoud, 2012) and number of adult social partners was related to theory of mind skill (Lewis et al., 1996) suggest this might be true.

A second hypothesis generated from social network theory is whether network diversity relates to children's social cognitive skill. It is possible interacting with out-group members will enhance children's communications skills because they must use these skills with more varied kinds of social partners. Prior developmental work has demonstrated that multilingual social environments effect social cognition and social learning (Barac & Bialystok, 2012; Byers-Heinlein & Werker, 2009; Howard et al., 2014; Yow & Markman, 2015). More specifically, prior work has shown that children in multilingual environments exhibit superior perspective-taking ability than children in monolingual environments (Fan et al., 2015) and this effect is observed in infancy as well (Liberman et al., 2016). This suggests that diversity and out-group exposure, as measured by network properties, might also relate to superior social cognitive skills.

This prior work suggests that social network size and network diversity should matter for children's early social cognition. A social network perspective will allow developmental psychologists to assess – does interacting with more people and more varied kinds of social partners give children more opportunity to use their social cognitive skills and therefore demonstrate superior social cognition? In Chapter 2, I will explore this hypothesis by asking whether Network Size and Network Language Diversity is related to 3-year-old's perspective-taking ability, a facet of theory of mind skill.

Intergroup Cognition

Social network theory generates the hypothesis that the diversity of the social network might relate to children's social bias and how they evaluate out-group members. The diversity of the network might affect children's own preferences and social bias, but it could also extend to affect their third-party expectations about who should socially affiliate. A network perspective can take this question a step further and ask whether the *stricture* of the diversity present in the social network relates to children's early social reasoning. For example, if racial diversity is related to children's racial preferences, does it matter how that diversity is patterned in the network? Does it matter if racial out-group members are more connected or more dispersed in the social network?

There is no prior work that has asked about whether the structure of diversity relates to intergroup cognition; however, there is a growing body of literature that has explored how variation in the diversity of social experience affects children's intergroup cognition. Children in more racially mixed schools are better at racial encoding (Weisman et al., 2015). Children in more racially diverse neighborhoods essentialize race less (Mandalaywala et al., 2019) and infants in more racially diverse neighborhoods are more open to racial outgroup members (Hwang et al., 2020). Children in more ethnically diverse communities essentialize ethnic identity less (Deeb et al., 2011). Children in racially diverse neighborhoods demonstrate less racial bias to out-group race members (Rutland et al., 2005). In addition to exploring racial diversity, researchers have also looked at how linguistic diversity affects social cognition. Children in linguistically diverse neighborhoods are more likely to imitate out-group members (Howard et al., 2014). Taken together, this suggests that the diversity of the social network might also affect children's intergroup cognition. I test this hypothesis in Chapter 3 by asking whether Network Racial Diversity is related to preschooler's racial friendship choices.

Overview of Dissertation

In the chapters to follow, I use the method I developed, *The Child Social Network Questionnaire*, to answer a few of the questions I outlined above. Chapter 1 will introduce *The Child Social Network Questionnaire* - a method for capturing infants' and young children's social networks. This chapter will argue that aspects of children's early social experience map onto social network dimensions. Data from over 300 children ranging from 6-months to 5-years-old will demonstrate that network dimensions can be used to capture and quantify early social environments. This chapter will articulate the ways that network properties map onto dimensions of early social experience and I will show how they vary across developmental time, social group membership, and childcare experience. Chapters 2 and 3 use this method to test some of the hypotheses laid out above. In Chapter 2, I test the hypotheses generated from social network theory about how network properties – Network Size and Network Language Diversity – relate to 3-year-old's perspective-taking (PT) ability. Results will show that Network Size is positively related to children's PT skill and exploratory analyses will suggest that Network Language Diversity has different effects on social cognitive skill in different sized social networks. In Chapter 3, I use preschooler's network properties to explore how Network Racial Diversity relates to children's racial friendship choices. Across several analyses, I find racial outgroup exposure is not created equal; how it relates to racial preferences depends on the Network Size, Network Structure, and the broader social environment.

Chapter 1: The Child Social Network Questionnaire

The period from infancy to early childhood is a time of rapid developmental change in social cognition and social skills (Hailey & Olson, 2013; Raabe & Beelmann, 2011; Trautner et al., 2005; Wellman, 2012). While there has long been interest in the effects of the social context on early social cognitive development, developmental science lacks a comprehensive tool to capture these richly textured experiences. In this chapter, I employ the tools of social network analysis as a way to capture and analyze the structure of children's social relationships, and provide descriptive social network data from children ranging in age from 6-months to 5-years-old to illustrate the ways in which network analysis can enrich developmental questions and provide new insight into the effects that social environments may have on early development.

A fundamental aspect of social experience is the day-to-day interactions that children have with other people. A number of studies have investigated aspects of these social relationships, for example the effects of contact with people from different racial groups on prejudice (Rutland et al., 2005; Weisman et al., 2015), the effects of multilingual social environments on social cognition and social learning (Barac & Bialystok, 2012; Byers-Heinlein & Werker, 2009; Howard et al., 2014; Yow & Markman, 2015), and the effects of siblings on social cognition (Jenkins & Astington, 1996; Kennedy et al., 2015; Perner et al., 1994).

Although there is substantial interest in understanding how variation in early social environments impacts social cognitive development, there is no unified framework to think about how social experience might affect children's social cognitive development. Prior developmental work has been limited in scope because it has only focused on one dimensional aspects of experience; how does a single aspect of experience relate to a social cognitive capacity? When early social experience is only conceptualized as isolated components, it is impossible to consider how various aspects of early social experience relate to each other. As stated above, there is evidence to suggest that exposure to multiple languages is associated with gains in social cognitive abilities; however, it is possible that multilingual environments covary with other aspects of experience that might be important for social cognitive development, such as interacting with more people outside the immediate family or interacting with a larger number of people on a regular basis. Another limitation of prior developmental work is that the methods used to quantify experience have been varied – everything from in-lab questionnaires, school demographics, or neighborhoods demographics to quantify "typical" experience or exposure. While none of these methods are incorrect, they conflate close personal relationships with more distal properties of the social environment, which makes it difficult to tease apart which kinds of experiences contribute to children's social cognitive development.

There is an excellent tool and framework commonly used in the social sciences to both describe social relationships, consider several aspects of social phenomena simultaneously, and to understand how social relationships impact an individual – Social Network Analysis. Network science has seen an explosion of research in the past several decades within social sciences, but also extending to other disciplines (Borgatti & Halgin, 2011). This explosion of research is seen within the psychological sciences as well, with substantial increases of network research in education (McPherson et al., 2001) and in social psychology (Clifton & Webster, 2017). Network theorists argue that we have seen this explosion of research because networks can be studied at multiple levels and social network analysis combines a great deal of rich data – both qualitative and quantitative – that make it an excellent tool for studying social phenomenon. Within the field of psychology, social network analysis has been used as a powerful tool to study a variety of groups – adults, adolescents, students in educational settings, and animals – and it is used to ask several different kinds of research questions. As examples, social network analysis has been used to ask questions about how classroom dynamics affect academic outcomes (Cooc & Kim, 2017), whether the presence of smokers in an adolescent's network will influence whether they become a smoker (Alexander et al., 2001), and to evaluate relations between social network size and brain function in adults and nonhuman primates (Bickart et al., 2011; Sallet et al., 2011). Social network analysis is a powerful and flexible tool, which makes it an excellent tool to study how the broader social context impacts an individual.

Yet, despite this increase of network research in psychological sciences, relatively little work has explored the personal social networks (also known as "egocentric" social networks) of infants and young children. This vacuum of research is striking given the longstanding interest in children's early social context among developmental psychologists. It is important to understand the composition of social networks for infants and young children because a child's social network captures most of their early social experience. From birth, infants are embedded in a rich social world that is filled with different kinds of social relationships. While infants certainly learn about the world through their own action (Piaget & Inhelder, 1969), infants come to learn about the social world through their social relationships; they gain social cognitive capacities by interacting with their social relationships and they learn about social conventions and rules by interacting and observing their social relationships (Gaskins & Paradise, 2010; Vygotsky, 1978).

To better understand the nature and breadth of early social relationships, we developed *The Child Social Network Questionnaire*. Social networks provide a novel, innovative tool to operationalize early social experience for infants and young children. In this paper, we argue that social network properties map onto dimensions of children's early social experience that are of interest to developmental psychologists; these properties can then be used to explore how experience relates to social cognitive development. *The Child Social Network Questionnaire* can be administered in infancy through early childhood to capture and describe experience. Descriptive social network data from over 300 children will demonstrate that networks are a powerful and flexible tool that can be used for all ages across developmental time.

Social Network Methodology and Terminology

Social Network Definition

Before describing my specific method, it is necessary to define the term social network. A social network is a set of objects and the connections between them (Wasserman & Faust, 1994). Network science shares a theoretical focus on ties between objects; however, there is a wide breadth of questions that can be asked using a network perspective (Perry et al., 2018). For this reason, the tools and methods of social network analysis are present across several different disciplines and used to answer questions at multiple levels of analysis.

Under this very broad definition of a social network, one can capture a myriad of potential phenomena and different kinds of networks. A social network could detail the connections between individuals at the level of the social system; for example, social networks have been used to ask about how romantic relationships in a particular high school related to the spread of sexually transmitted diseases amongst students (Bearman et al., 2004). This kind of network can also be explored in animals; a study of endangered killer whales discovered that in years of high food availability, there was more interconnectedness in the social network of whales (Foster et al., 2012). These networks are called sociocentric networks (Perry et al., 2018). A social network perspective could also be used to explore how population-level characteristics relate to individual behavior; for example, a study with cowhead birds showed that birds in dynamic social networks, where individuals were replaced over time, had more reproductive success than birds in a static social network (Gersick et al., 2012; White et al., 2010). A social network could also delineate the people emotionally close to or immediately surrounding an individual; these are called egocentric networks and these are the networks that psychologists typically care about (Perry et al., 2018; Robins, 2015). For example, psychologists have used social networks to ask how the size of the social network relates to adults' perspective-taking skill (Stiller & Dunbar, 2007).

The idea of a network and the tools for analyzing networks can be applied at different scales and in different settings. The research question defines the network space and defines who should be included in the network (Borgatti & Halgin, 2011). To best understand the potential effects of social experience on early social-cognitive development, it is important to focus on children's recurring, everyday contact with other people. *The Child Social Network Questionnaire* uses parent interview to identify the people with whom the child interacts during a typical week of activities. For the rest of this dissertation, the term "social network" refers to children's personal, recurring social relationships. Following the terminology of network theory, the people that are included in these networks will be referred to as "nodes" or "alters" (Robins, 2015).

Network properties can be used to describe aspects of early social experience that developmental psychologists care about; such as the prevalence of emotionally close relationships in children's everyday social experience or the racial or linguistic diversity of children's early social environments, as well as previously unexplored dimensions of early social experience, such as how individuals are connected to one another in the network. There are three dimensions of a social network that map onto children's early social environments: the relationships between the alters and the child, the attributes of the alters, and the relationships among the alters (Perry et al., 2018). These dimensions of social networks describe both the composition of the social network (e.g., How many females are in the network? How many adults?) and the structure (e.g., What is the size of the social network? How fragmented or connected is the network?).

Before describing the specific measures from the descriptive data, I provide high-level summaries of the dimensions of social networks and demonstrate how they can be used to capture and describe children's early social environments.

Dimensions of Networks to Describe Early Social Environments

The relationships between the alters and the child. The first dimension of social networks that is useful to describe early social experience is the relationships between alters and the child (Figure 2). The most basic summary of a social network is **social network size**. Social network size is the number of alters that a child is connected to (Perry et al., 2018). Social network size is an important aspect of children's early social experience because it captures the number of unique individuals a child interacts with on a regular basis. This is important to capture because these are the people who will provide the most input to the child as well as be the different social groups children are exposed too.

Another summary measure that is useful to describe early social experience is **relationship strength**. Relationship strength in adults is a combination of time spent with an individual, the emotional intensity, as well as mutual confiding; each relationship can be described as either a *strong* or *weak* tie in the network literature (Campbell et al., 1986; Granovetter, 1983). Strong ties are relationships where an individual has a strong emotional connection and spends a lot of time with that person, such as family or close friends. Weak ties are relationships where an individual does not have a strong emotional connection and does not spend as much time with that person. Each relationship a child has with an alter can be measured for the intensity; a summary measure can be created about the intensity of the relationships in the network per child by aggregating across the relationships. This measure can describe the extent that children vary in the intensity of their social relationships. For children, their strong ties will be family and people that spend a lot of time with the child. Weak ties will be people that children see less frequently, such as a music class instructor or the librarian at Story Time.

The attributes of the alters. Another dimension of social networks that is useful to describe early social experience is the attributes of the alters (Figure 2). The attributes of the alters can be anything the researcher would like to know about the individual alters – their race, gender, languages they speak, age, social status, education, religion, even common interests or shared beliefs. Similar to the relationships between alters and child, we can aggregate information across the attributes of the alters to get a summary measure about the attribute per network or child. For example, using social network analysis can assess the proportion of males and females in the network, the racial diversity of the network, the proportion of kin relationships, and so forth. The summary measures of these attributes make up the diversity in children's social networks, and therefore, their early social environments. The different social groups that children have regular contact with can be assessed by looking at the attributes of the alters.

Measures of diversity. Diversity in a social network can be described in at least two conceptually distinct ways. Network diversity measures can be used to both 1) describe the representation of different groups or categories in the network and 2) how diverse the network is relative to the child's own attribute. The measure used to describe the representation of different groups or categories is ***entropy***. Entropy is commonly used in social sciences to describe the representation of different categories (Proops, 1987; Shannon, 1948). For network science, entropy indicates the relative presence of different social categories among the alters in a network. A score of 0 indicates that there is no diversity of categories; all the alters share the same attribute (i.e., all the alters are the same race). A higher entropy scores indicates a greater representation of different categories (i.e., the racial entropy for the network in Figure 2 would be 0.86; see Figure 5 for example networks and scores).

The measure used to describe the diversity of the network relative to the child's attributes is the **EI Index.** "E" stands for external or different alters and "I" stands for internal or same alters; each alter in the network is classified as either "same" or "different". The EI Index is a measure of homophily the child shares with the network and is calculated as follows: *(Number of Different Alters – Number of Same Alters)/Network Size* (Krackhardt & Stern, 1988). The EI Index ranges from -1 to 1; a score of -1 indicates the entire network is the same as the child on some attribute and a score of 1 would indicate that the entire network is different from the child on some attribute. For the network in Figure 2, the White child has 5 alters that are White and 2 that are Black, so they would have a score of (2 – 5)/7 = -0.43 for their racial EI Index (see Figure 6 for more examples).

Entropy and EI Index can be used to describe the representation of diversity in the network, as well as how diverse the network is relative to the child. Network measures allow developmental psychologists to be precise in describing diversity and explore the ways different kinds of diversity affect social cognitive development. While these network diversity measures can be used to describe a whole host of attributes (e.g., race, gender, language, religion, political ideology, etc.) for this chapter, I focused on the racial and ethnic and linguistic diversity of children's social networks. The present study was conducted with children in the US and race/ethnicity and languages spoken are two salient social groups in US society.

The relationships among alters. A final dimension of social networks that is useful to describe early social experience is the relationships between the alters, which is the network structure (Figure 2). The relationships between the alters (alter-alter) is a different dimension than the relationships between alters and the child (alter-child). Relationship strength can be easily calculated for alter-child relationships, but this is harder to assess for alter-alter relationships. It is difficult to have parents provide subjective ratings about a relationship between two other people and it introduces measurement error; proxy reporting is often biased by their own experiences with the alters (Blair et al., 2004; Epley, 2008; Perry et al., 2018). The alter-alter relationships are still informative for describing early social experience because they can be used to describe the patterns of relationships present in children's social networks. The alter-alter relationships determine the structure of the social network; they can be used to describe how connected the network is as a whole and how fragmented the network is in space.

Measures of structure. Network structure can be described in two ways. The most basic structural measure of a social network is to describe how connected the network is or how connected all the alters are in a network – this is measured by **density** (Perry et al., 2018). While the child is connected to all the alters, not all the alters are necessarily connected to each other (see Figure 2). A network where all the individuals know each other would have a density score of 1. A value less than 1 means that not all the alters know each other – the lower the number, the less connected the network.

Networks can also be described by how fragmented they are in space. For example, the network in Figure 2 shows two different circles of people that interact. The network measure to describe the fragmentation is the **component ratio** (Perry et al., 2018). A component emerges when alters know each other and are all connected to each other. Every child has at least one component. Early in life, these are the family members that live with the child. As the child gets older, they start to interact with people that might not all know each other. For example, if the child goes to daycare, that would be another component – all the people the child interacts with at daycare know each other, but they do not necessarily know every member of the child's family. Components are used in network science to assess how fragmented or spread out the network is. Larger networks tend to have more components, so to account for Network Size the component ratio is calculated as follows: *(Number of components – 1) / (Network Size – 1)* (Perry et al., 2018). Larger values of the component ratio indicate that the network is more fragmented. A score of 0 in this dataset indicates that the child only interacts with family members because they only have one component.

The Present Study

We developed *The Child Social Network Questionnaire* to collect social network data from children in infancy through the first few years of life. The present study applies the tools of social network analysis to children living in the US, largely in and around a large city. The analysis presented below sheds light on the ways in which children's social networks may change across early development and the extent to which there is variation in these aspects of early social experience. We recruited over 300 children across the first few years of development to ensure we would be able to explore the complex and embedded nature of early social environments.

The descriptive social network data will answer five important questions. First, I provide descriptive information about the network variables to explore the nature of the dimensions of early social experience in the first few years of life and present an analysis of the complexity of social networks; this analysis will provide examples of how social networks can be used to describe several dimensions (such as the network diversity and the network structure) of children's early social environments in a unified framework. After describing the nature of children's social networks, the next analysis will explore how social networks vary by social group membership of the child. This analysis will explore how properties of early social environments vary for children in different social groups; this analysis will inform hypotheses about how experience might differentially affect children in different social groups. The third analysis will ask, how do social networks vary with age? This analysis will provide a cross-sectional look at how dimensions of early social environments might change in the first few years of life – a time when children are experiencing rapid changes to their cognition. The fourth analysis will ask how do social networks vary with daycare or school experience? In addition to asking questions about how social network properties change across developmental time, this analysis will explore whether network properties differ for children with out-of-home childcare experience. Finally, the analysis will explore how network and neighborhood diversity measures relate to each other. As highlighted above, prior developmental work has conflated close social relationships with more distal social environments. Social network data can be used to highlight the extent that network and neighborhood demographics map onto each other.

Methods

Participants

The participants were recruited in two places. The first group of participants (*n* = 209; M_{age} = 24.9 months; range: 6.4 – 59.1 months) were tested in a developmental laboratory in Chicago, Illinois; these were families from the city of Chicago and the surrounding suburbs who volunteered to be in a database for those interested in early childhood research. The second group of participants were recruited at a paid-to-enter public museum setting in Chicago, IL (*n* = 108, M_{age} = 48.1 months; range: 36 – 59.4 months). A total of 37 subjects were excluded from the final data analysis due to experimenter error in conducting the interview (*n* = 30) or parents not being able to provide complete data during the parent interview (*n* = 7) for a total final sample of 280 children (M_{age} = 33.3 months, range: 6.4 – 59.4 months). The museum is a destination spot for tourists who visit Chicago, so while 75% of our participants were from Chicago and its surrounding suburbs, 25% were from other areas in the United States. Parents reported their children were 56.0% White or European-American, 15.2% Black or African-American, 7.1% Asian or Asian-American, 9.9% Hispanic or Latino/a-American, 19.9% mixed or biracial, and 3.2% as Other. For the laboratory-tested subjects only, we recorded maternal education and 74.3% of those children had mothers with a bachelor's degree or higher.

The Child Social Network Questionnaire

The Child Social Network Questionnaire is a novel method we designed to assess infants' and children's social networks. *The Child Social Network Questionnaire* (CSNQ) is administered in two parts: 1) a parent interview to collect information about children's typical week of activities and 2) a form to collect demographic information for each person the child sees on a regular basis; this form is used to calculate the network measures described above. In network terminology, the parent interview is the "name generator" - this is the method or tool used to elicit each of the people that should be included in the social network. The people in the social network are called "nodes" or "alters" (Robins, 2015). The demographic information is the "name interpreter" and this is the method used to collect the basic demographic information about each of the alters. This is known as the attributes of the alters (Perry et al., 2018).

Parent Interview

For the parent interview parents were asked to describe their child's "typical week" of activities. The interview was explained as follows: "First, we will do an interview where I will ask you to describe [CHILD's] typical week. We want to understand the different people [CHILD] sees in a typical week and what kinds of activities he/she does with those people. I am going to ask you about times [CHILD] wakes up, goes to sleep, and takes a nap so we can get a rough measure of the amount of time they spend with different people. After the interview, I will create a form for each of the people you mentioned to collect basic demographic information and also questions about how close you think your child is to that person. Starting with Monday, what time does your child wake up and what happens after that?" The goal of the parent interview was to generate a list of people the child interacts with on a regular basis. Parents' description of their child's typical schedule served as a memory prompt and allowed the experimenter to make sure all the individuals a child knows are accounted for (see Appendix A for more specific details about the parent interview). By having parents go through and describe the events they do during the week and not just recall individual people, we ensured that parents were reporting all the social contacts children have in a week. This method of recall prevented parents from underestimating the value of the weaker ties in the social network (Small, 2017). After parents described their child's schedule for Monday through Sunday, the experimenter asked, "Is there anyone else that you think is worth mentioning that your child sees on a regular basis?" There are two things that can be determined from the parent interview: 1) a list of the people the child interacts with on a regular basis, which is the child's social network size and 2) the proportion of the child's waking hours the person spends with the child. After the parent interview, parents completed a demographic survey for each of the people in their child's social network. Parents completed the demographic form in-person (n = 249) or in a follow-up, online form (n = 31).

Demographic Form

There were two different versions of the demographic form for laboratory testing and public museum testing. Laboratory testing allows for longer questionnaires to be administered to families. In a public museum setting, the studies that children participate in need to be quick, so the demographic form needed to be shortened so the entire *Child Social Network Questionnaire* only took 5-10 mins to complete. For both laboratory and museum testing, the form asked about basic demographic information for each person: gender, age, race, and languages the person speaks. For laboratory testing only, the form collects information about the intensity of the relationships. For example, it asks questions about how many different activities each person does with the child and how emotionally close the child feels toward that person (see Appendix B). For museum testing only, the form asks about the different contexts or settings each person interacts with the child. This question allows us to compute the density, or how connected the network is, for each child[2] (see Appendix C).

Network Variables

Network Size

Network Size was defined as the total number of unique individuals and groups a child saw on a weekly basis. A parent had to report that the child knew the person as an individual for that person to be their own node. For example, if the parent reported that the child was in daycare or preschool, the experimenter would ask, “Are there any kids in the class that stand out as

[2] Another aspect of social relationships that can be assessed is whether the tie is “positive” or “negative”. This is not a dimension assessed by the CSNQ given the difficulty in determining what a negative tie is for infant relationships. See Robins (2015), especially chapter 2, for more information about positive and negative ties.

friends?". In addition to the individual named friend nodes, there would also be a node for "daycare/preschool class", which is a node that includes multiple people. This distinction was made in order to capture the network of people that the child "knows"; these are the people that are closest to the child. For adults, the social network of an individual is a hierarchy that can be conceptualized as concentric circles (Hill & Dunbar, 2003; Sutcliffe et al., 2012); this method allowed us to capture the inner most circle for children. In the network science literature, the research question determines the boundaries of the network (Borgatti & Halgin, 2011). Social networks are most useful for developmental psychologists if they capture children's recurring social contact; therefore, the network space we were interested in is who the child knows and has regular contact with.

High and Low Intense Relationships

For the laboratory-based subjects (n = 161), there were three measures to assess the intensity of the relationship: the number of activities the person does with the child, how emotionally close parents reported their child feels toward the person, and the proportion of waking hours the person spends with the child (see Appendix B). A z-score was calculated across all 1232 relationships for each of the three measures and an average z-score was computed for each relationship. A median split of the average z-score then classified each relationship as either "low" or "high" intensity (see Figure 3 for the distribution of z-scores for all the social relationships).

Proportion of Kin and Adult Relationships

Each relationship was also classified as being kin or not kin. Kin is any relationship in the immediate and extended family (including grandparents, aunts, uncles, cousins, etc.). The proportion of kin relationships was calculated for each child's social network: number of kin relationships/total Network Size. Each relationship was also classified as either being an "adult" or "child" relationship. Child in this sample was anyone under the age of 13. The proportion of adult relationships was calculated for each child's social network: number of adult relationships/total Network Size.

Network Diversity Measures

As described above, entropy and the EI Index were calculated for both racial diversity and linguistic diversity. Entropy described the representation of different social groups in the network and the EI Index indicated how diverse the network was relative to the child. Both entropy and the EI Index were calculated using the egor package in R (Krenz et al., 2020).

Entropy. For network science, entropy indicates the relative presence of different social categories among the alters in a network and is calculated as follows for a given probability vector of P(X): $H(X) = - \sum P(X) * log2(P(X))$ (Drost, 2018; Krenz et al., 2020; Shannon, 1948). A score of 0 indicates that there is no diversity of categories; all the alters share the same attribute (e.g., all the alters are the same race). A higher entropy scores indicates a greater representation of different categories (i.e., the racial entropy for the network in Figure 2 would be 0.86; see Figure 4 for example networks and scores).

Network Racial Entropy. In order to calculate racial entropy, each alter needed to be classified by a discrete racial category. The racial categories that were used to calculate entropy were the following: African or Black-American, Asian or Asian-American, European or White-American, Hispanic or Latino-American, Native American, Mixed/Biracial, or Other. For the Mixed/Biracial category, parents could indicate that the alter was biracial by selecting "Mixed/Biracial" or by selecting more than one race. For some alters, we have detailed information (for example, if the alter was a Black/White biracial or Asian/White biracial), but for some alters we only have that they are biracial. As such, all biracial alters were categorized as "Mixed/Biracial". This is imperfect as biracial individuals are not a monolith; however, this method of categorization allowed us to retain all the racial information about the alters.

Network Language Entropy. Similar to the Racial Entropy, each alter needed to fit into a discrete language category to calculate language entropy. This is a primarily English-speaking sample; all the children were recruited to participate in studies in English and required that English be spoken at home at least 50% of the time. The most dominant language category was monolingual English speakers (66.3% of all alters), followed by English bilingual speakers (22.5% of all alters), preverbal infants (1.7% of all alters), and non-English monolingual speakers (1.0% of all alters). Language data was missing for 8.5% of the alters and they were excluded from analysis.

EI Index. The EI Index is a measure of homophily the child shares with the network and is calculated as follows: *(Number of Different Alters – Number of Same Alters)/Network Size* (Krackhardt & Stern, 1988; Krenz et al., 2020). The EI Index ranges from -1 to 1; a score of -1 indicates the entire network is the same as the child on some attribute and a score of 1 would indicate that the entire network is different from the child on some attribute (e.g., if a White child had a network where all the alters were White, they would get a score of -1; see Figure 5 for example).

Racial EI Index. To calculate the racial EI Index, each alter had to be classified as either same-race or different-race compared to the child. For monoracial children, this was simple – any alter that was not the same-race as the child was coded as different-race (i.e., for a White child, any alter that was not also White was coded as different-race). For biracial children (19% of our sample; n = 51), the alter was classified as same if they were either races of the child. For example, for a Black/White biracial child any alter that was White or Black would be coded as same. All other alters would be coded as different. For our biracial children, parents either provided detailed information for their child or we could deduce the races of the child by looking at the races the parents reported for themselves.

Linguistic EI Index. For the Linguistic EI Index, each alter was coded as same-speaker or different-speaker. For monolingual English children, this meant anyone who spoke a language other than English was coded as different-speaker. For bilingual and multi-lingual children, an alter was coded as different-speaker if that person spoke a language the child did not speak. For example, imagine an English/Spanish bilingual child with a network where 2 people spoke English, 1 spoke English and Spanish, and one spoke English and Dutch. The only alter that is a different-speaker is the English/Dutch bilingual because the child does not speak Dutch and would therefore have a Linguistic EI Index of -0.5 ([Different-speaker – Same-speaker]/Network Size; [1 – 3]/4).

Network Structure

Density. The most basic structural measure of a social network is density. Density is a measure of the degree of connectedness of alters in the network and was calculated as follows where T is the number of ties[3]: $Density = 2T / N(N-1)$ (Perry et al., 2018). A network where all the individuals know each other would have a density score of 1. A value less than 1 means that not all the alters know each other – the lower the number, the less connected the network. For the museum sample only (n = 101; M_{age} = 48.1 months; range: 36 – 59.4 months), we could calculate density because the CSNQ included a question asking about the different contexts that the

[3] Ties are classified as "undirected" or "directed". Undirected ties indicate whether there is a relationship between two alters. Directed ties indicate whether the tie is reciprocal or one-sided between 2 alters (see Robins (2015) chapter 1 for more information). The CSNQ focused on undirected ties, given the difficulty in defining what reciprocity means for infant social relationships.

individuals interacts in with the child. Example network graphs are presented below to understand what the density values represent visually (Figure 6).

Number of Components. Another way to describe the structure of the network is the number of components. A component emerges in the network when all the alters are connected to each other in some way (Perry et al., 2018). In an egocentric network, a component emerges when all the alters are connected even when you remove the child. For example, for the child in Figure 1, if you were to remove to the child, the Mother, Father, Sister, and Nanny all still interact with each other. In Figure 6, the child on the left has 4 components and the child on the right has one component. In the adult literature, this is typically assessed by asking an ego to report on all the pairwise relationships of who knows who (Perry et al., 2018). Adding those questions to the CSNQ would have made the survey considerably longer and therefore more time consuming to administer in the laboratory along with child assessments. To assess the components in a child's network, we asked about the different activities the child did throughout the week. The different activities were the components – for the activities, all the people at that activity would know each other. Every child has at least one component. Components are used in network science to assess how fragmented or spread out the network is in space. Children with just one component only interacted with family members. Children with more than one component had family and some other activity such as daycare, school, library story time, gym daycare center, ninja class, neighborhood potlucks, Sunday School, Chinese class, art class, or playgroup, just to name a few.

Component Ratio. Finally, a social network can be described by how fragmented the network is in space. In Figure 6 above, the network on the left is more fragmented and spread out then the network on the right. The measure to describe how fragmented a network is called the

Component Ratio. Larger networks tend to have more components, so to account for network size the Component Ratio can be calculated as follows where C is the number of components: *(C – 1) / (Network Size – 1)* (Perry et al., 2018). Larger values of the component ratio indicate that the network is more fragmented.

Neighborhood Demographics

In addition to completing *The Child Social Network Questionnaire*, parents also provided the zip code of where their child lived. Using data from the US Census (American Community Census Survey from 2018), we were able to extract Neighborhood Racial Entropy and Neighborhood Linguistic Entropy for each child (Hwang, 2018). 65% of our sample lived in an urban setting with a median income of $68,770 (range: $28,965 - $196,964).

Results

The results presented below will accomplish the following aims. First, we present the descriptive information about the network variables and how they connect to each other, as well as provide an analysis of the complexity of social networks; this analysis will demonstrate the power of considering several dimensions of children's early social environments in a unified framework. Next, we will answer the following questions: How do social networks vary by the social group membership of the child? How do social networks vary with age? How do social networks vary with daycare or school experience? How do network and neighborhood diversity measures relate to each other?

Social network data tends to be skewed and colinear, given the nature of social phenomenon (Perry et al., 2018); therefore, we used non-parametric analyses for network variables that were not normally distributed.

Social Network Variables

Table 1 shows the mean, standard deviation, and range for the following network variables of interest: Network Size, Raw Number of Low and High Intense Relationships, Proportion of High Intense Relationships, Proportion of Kin Relationships, Proportion of Adult Relationships, Density, Number of Components, Component Ratio, Racial Entropy, Racial EI Index, Language Entropy, Language EI Index. For visual examples of the network structure values, refer to Figure 6. See Figure 4 and 5 for visual examples of entropy and the EI Index.

Kin Relationships and Intensity

Kin relationships are typically thought of as close relationships and have significant universal and evolutionary importance (e.g., Hamilton, 1964). Although children's explicit understanding of kinship relationships are slow to emerge, 15- to 18-month-olds expected two adults that comforted a crying infant to affiliate, suggesting that infants are sensitive to caregiving situations and how individuals are embedded in a large social system (Spokes & Spelke, 2017). This dataset allowed us to explicitly test whether kin relationships were also high intense ones in early childhood.

Table 2 shows a 2x2 contingency table of the count of relationships by whether they were kin relationships and whether they were high or low intense relationships across the entire sample. On average, approximately half of children's relationships were high intense and half the relationships were kin (Table 1); however, Table 2 highlights that not all kin relationships were necessarily high intense. Children had some non-kin relationships that were high intense relationships, such as daycare teachers, and they had kin relationships that were low intense, such as extended family members. We also looked to see if the Proportion of Kin relationships was correlated with the Proportion of High Intense relationships and found a positive correlation; networks with a larger proportion of kin relationships were also networks that had a larger proportion of high intense relationships (*rho* = 0.42, $p < 0.001$). Consistent with the implicit assumption, proportion of kin relationships were related to proportion of high intense relationships for children's early social networks.

How Do the Network Variables Correlate with Network Size?

As network size increases, other aspects of the network tend to covary as well. Network structure measures are inherently linked to network size – as network size increases the number of components typically increases while the density of the network decreases (Perry et al., 2018). Table 3 presents the FDR corrected correlations between Network Size and the other network properties. Consistent with the adult social network literature, network size covaried with network structure – as the network size increased, the number of components increased (*rho* = 0.63, $p < 0.001$) and the density of the network decreased (*rho* = -0.52, $p < 0.001$). As network size grew, children had more contexts that they interacted in and the connectedness of the network decreased. The content of the network also covaried with size. As network size increased, the proportion of high intense relationships (*rho* = -0.41, $p < 0.001$), the proportion of kin relationships (*rho* = -0.56, $p < 0.001$), and the proportion of adult relationships (*rho* = -0.38, $p < 0.001$) all decreased. As network size grew, children interacted with more low intense relationships, more children, and more people outside of their family. Finally, the diversity measures also covaried with network size. As network size increased the racial entropy (*rho* = 0.35, $p < 0.001$), racial EI Index (0.24, $p < 0.001$), and linguistic EI Index (0.24, $p < 0.001$) increased as well. As network size increased, so did the various measures of diversity.

This correlational analysis demonstrates that social environments and social phenomenon are complex and embedded. While several of these dimensions of early social experience are conceptually distinct, this analysis shows they can also be empirically related. When using social network analysis and theory as a framework to understand how social experience relates to development, it is necessary to understand which aspects of experience covary.

How Does Network Diversity Interact with Structural Network Properties?

The benefit of social network analysis is that it can be used to describe how the variables are related to each other. For instance, the network racial diversity can be described by using the two measures outlined above – racial entropy and racial EI Index. These measures perfectly describe the racial diversity of children's close personal relationships; these measures allow psychologists to define the racial exposure of children's close, personal contact. Social network analysis can take this one step further to ask: how are different racial group members patterned in the social network? Is children's contact with racial outgroup members interconnected or more dispersed in the social network?

Using the museum subjects (n = 101; M_{age} = 48.1 months; range: 36 – 59.4 months), we could calculate the Racial Entropy of the network, but also the Racial Entropy of each of the components. Children ranged in the number of components they had – anywhere from 1 to 7 – and for each child, we could calculate the proportion of their components that had 0 entropy. A component that had 0 entropy meant that all the people in that component were the same race. A child with a proportion of 1 would mean all the components in their network had a racial entropy score of 0, which would indicate a no diversity network. A child with a proportion of 0 would mean that all the components had a racial entropy greater than 0 – all the components had people of different races. The average proportion of 0 entropy components per child was 0.31 (SD = 0.30, range: 0-1; Figure 7).

Once the racial entropy of each component was calculated, it was then possible to identify different patterns of diversity that emerged. Table 4 highlights examples where subjects had identical overall Network Racial Entropy, but the racial diversity was patterned differently in the network. For example, Subject1 and Subject2 had the same overall Network Racial Entropy; however, Subject1 had a network where the racial diversity was not evenly distributed. Their family did not provide any racial diversity, but they had fairly high racial diversity at school. On the other hand, Subject2 had high levels of racial diversity across all their components; their social network was more racially integrated. Table 4 highlights that the Network Racial Entropy glosses over complexity present in children's social relationships. Not only can the network be described by the composition of different social groups, but networks can also be used to explore how the pattern of those relationships might matter and impact social cognitive development.

Children's networks could further be characterized by how the racial diversity was distributed in the network – did children experience racial diversity in an integrated network, where there was non-zero entropy in each component, or did children experience racial diversity in a segregated way – where some components had no racial diversity and other components did? Each child's network could be described as either integrated, segregated, or no diversity networks. Integrated networks meant that the overall network racial entropy was greater than zero and each component in the network also had network racial entropy greater than zero. A segregated network was when the overall network racial entropy was greater than zero and the proportion of zero entropy components in the network was greater than or equal to .5, but less than 1 (Figure 8). A no diversity network meant that the overall network racial entropy was 0 – all the people in the child's network were the same race and therefore each component also had 0 racial entropy. For this sample, 40% of the children had an integrated network, 54% had a segregated network, and 6% had no diversity networks. This sample of preschoolers demonstrated that racial diversity can be patterned in several different ways. This raises the interesting question about whether *how* racial outgroup members are patterned in the social network matter for children's emerging intergroup cognition.

How Do Social Networks Vary by the Social Group Membership of the Child?

The data was further analyzed by whether the network properties varied by children's social group membership. It remains an open question whether and how the early social environments vary for children in different social groups. For example, does the racial diversity of close relationships vary for racial majority versus racial minority children? For adults, there are differences that emerge based on race. For example, there is robust network literature that shows Black American adults typically have smaller social networks than White American adults (Hedegard, 2018; McPherson et al., 2001; McPherson et al., 2005). This is important to describe in children because network composition can have a differential impact for adults of different races. For example, White Americans in large social networks described their ethnic identity as less important to them than those in smaller social networks, and biracial adults whose parents were Black and White identified more strongly with being Black when Black people were more represented in their social network (Rockquemore & Brunsma, 2002). In addition to describing children's network properties by child race, we also present how the networks properties vary by whether the child is a monolingual or multilingual speaker. There is robust literature that describes the different kinds of linguistic input children receive (Rowe, 2008; Shneidman et al., 2013; Weisleder & Fernald, 2013) and how bilingual speakers exhibit superior executive function (Bialystok et al., 2009; Kovács & Mehler, 2009), but less is known about the kinds of speakers children interact with on a regular basis. The data presented below starts to answer these questions.

Table 5 shows the mean, standard deviation, and range of Network Racial Diversity by child race. Only three children in this sample reported their race as "Other". We present the means and standard deviations, but cannot make any strong conclusions for these children. For Racial Entropy, biracial children had the highest values ($M_{RacialEntropy} = 1.46$), which is unsurprising. Biracial children by definition have two parents that are different races, so they typically have networks with higher entropy, and that is true in this sample. Black children and Hispanic children had the least amount of Racial Entropy ($M_{RacialEntropy} = 0.60$). For the Racial EI Index, all racial subgroups had a mean score less than 0. This indicates that on average, children in this sample had networks that were more same-race as them. Asian children had the highest value ($M_{RacialEI} = -0.27$), but notably still less than 0. White, Black, Hispanic, and Biracial children had networks at approximately -0.5, which indicates that on average networks tended to be more same-race as the child.

Table 6 presents the other network properties by whether the child was a racial majority (White) child ($n = 153$) or a racial minority child ($n = 125$). Wilcoxon Rank t-tests were performed with FDR corrections. The results showed that racial minority children had a higher proportion of kin in their networks ($M_{Racialminority} = 0.57$, $M_{White} = 0.48$; $W = 7750$, $p < 0.05$), less components in their networks ($M_{Racialminority} = 2.35$, $M_{White} = 2.68$; $W = 10936$, $p < 0.05$), and had less fragmented networks than White children ($M_{Racialminoirty} = 0.14$, $M_{White} = 0.16$; $W = 10511$, $p < 0.05$). The observed differences in the proportion of kin in the network could explain the differences that are observed with the network structure measures. Networks that have a higher proportion of kin likely have more people that know each other across the network, which could explain why there were slightly fewer components and less fragmentation for the racial minority children.

The Complexity section reports the proportion of the museum-based subjects who had either integrated, segregated, or no diversity networks. A chi-square test of independence was performed to examine the relation between child race and network pattern type and the relation between these variables was not significant; there was no evidence to suggest that child race was related to different network patterns for preschoolers (X^2 (1, N = 98) = 2.89, p = 0.24). 52% of White preschoolers had integrated networks, 44% had segregated networks, and 4% had no diversity networks. 64% of racial minority preschoolers had integrated networks, 28% had segregated networks, and 8% had no diversity networks.

Table 7 shows how the network properties varied by whether the child was a monolingual English speaker (n = 146) or a multilingual speaker (n = 119). Wilcoxon Rank Sum tests were performed with FDR corrections to compare the networks properties of monolingual versus multilingual speakers. The only differences between the two groups were for the Language Diversity measures; multilingual speakers had higher language entropy (a greater representation of different language speakers; $M_{Monolingual} = 0.48$, $M_{Multilingual} = 0.96$; $W = 2980$, $p < 0.05$) and also more negative values of the Linguistic EI Index (more of their network was same-language speaker as them; $M_{Monolingual} = -0.74$, $M_{Multilingual} = -0.81$; $W = 6033$, $p < 0.05$).

Finally, we conducted an analysis on children's friendship networks to explore the racial and linguistic diversity of friendship networks. An alter was considered a friend if the parent named a specific child during the interview. On average, children had 1.7 friends (SD = 2.0, range: 0-10) and the number of friends children had increased with child age ($rho = 0.57$, $p < 0.001$). Wilcoxon Rank Sums t-tests were performed with FDR corrections to test whether the diversity measures differed for children in different social groups. Table 6 shows the mean and standard deviation for the Friendship Racial Entropy and Friendship Racial EI Index for racial majority versus racial minority children; there was no evidence that the racial diversity measures varied for children based on child race (Friendship Racial Entropy: M_{White} = 0.52, SD_{White} = 0.59, $M_{Racialminority}$ = 0.48, $SD_{Racialminority}$ = 0.53, W = 2793, p = 0.97; Friendship Racial EI Index: M_{White} = -0.35, SD_{White} = 0.69, $M_{Racialminority}$ = -0.31, $SD_{Racialminority}$ = 0.77, W = 2246, p = 0.88). Table 7 shows the mean and standard deviation for the Friendship Language Entropy and Friendship Linguistic EI Index. While there was no significant difference in the Friendship Language Entropy ($M_{Monolinguals}$ = 0.17, $SD_{Monolinguals}$ = 0.36, $M_{Multilinguals}$ = 0.28, $SD_{Multilinguals}$ = 0.44; W = 2478, p = 0.13), results revealed a significant difference in the Friendship Linguistic EI Index – monolingual English speakers had friendship networks that were more similar to themselves than multilingual speakers ($M_{Monolinguals}$ = -0.11, $SD_{Monolinguals}$ = 0.97, $M_{Multilinguals}$ = 0.46, $SD_{Multilinguals}$ = 0.78; W = 1930, $p < 0.001$). Multilingual speakers had more friends that spoke languages different than them. Not only do multilingual children have different language environments by the nature of the languages they themselves speak, but the kinds of different speakers they are surrounded by tends to be different as well.

Summary of Analysis by Children's Social Group Membership

For both racial and linguistic diversity measures, there were interesting trends that emerged across the two measures of diversity for children in different social groups. The Racial EI and Linguistic EI Index looked similar for children across social groups – most children, regardless of race or languages spoken, had networks that tended to be more same-race and same-language speaker as them. This was especially true for multilingual speakers compared to monolingual speakers. Interestingly, the racial entropy and language entropy differed by social groups. Although descriptively racial minority children had higher racial entropy than racial majority children, the trend was not statically significant. On the other hand, multilingual speakers had greater language entropy than monolingual speakers; multilingual speakers had networks with a greater diversity of different kinds of language speakers.

These data highlight the power of social networks as a tool to describe diversity. The data presented here suggest that these conceptually distinct ways to measure diversity varied in significant ways. The entropy measure of diversity showed variability across children of different races and mono- and multi-lingual speakers; the representation of different social categories varied by children's social group membership. The EI Index measure of diversity demonstrated a different pattern. Across racial subgroups, the networks tended to be more same-race than different-race from the child (Table 5). Across mono- and multilingual speakers, the networks tended to be more same-language speaker as the child as indicated that both groups of speakers have scores that are less than 0; this trend was particularly true for the multi-lingual speakers. Interestingly, the multilingual speakers had friends that were more different language speakers than the monolingual speakers. These data highlight the importance of using social networks as a tool to describe diversity and suggest that measures of diversity could vary based on children's own social group membership.

How Do Social Networks Vary with Age?

Descriptive social network data collected over a wide developmental age range can answer the question: how does early social experience vary with age? The analysis presented below demonstrates how network properties, which describe early social environments, vary across developmental time. The analysis presented below used FDR correction for multiple comparison. As noted below, some of the network variables were skewed and transforming the variables did not make the distributions normal. In these cases, we conducted non-parametric analyses.

Network Size and Age

Network Size was correlated with child age to explore how the number of people a child interacted with on a regular basis varied across the first few years of life. Network Size was square root +.5 transformed because Network Size is a small count variable (Kirk, 2013). The results showed a significant, positive correlation between Network Size and age; as children got older their Network Size increased ($rho = 0.61$, $p < 0.001$; Figure 9). At a time when children are experiencing rapid changes to their social cognitive development they are also experiencing drastic changes to their early social environments. The number of close, reoccurring social relationships children had increased over the first few years of life.

Even during the first few months of life, infants saw an increase in their network size as they got older. This growth in network size was seen before children attended school and continued to rapidly grow after children attended school (Figure 19; see below). In addition to the tremendous growth in size during the first few years of development, there was also substantial variation at any given time point. This variability was present in infancy and continued throughout early childhood. Taken together, this raises two interesting possibilities. First, at a time when children see a rapid expansion in the number of social relationships they interact with on a regular basis, they are also experiencing rapid changes to their social cognition. Their social cognitive skills start to emerge and mature during the first few years of life, which raises the question about how the growth in network size relates to the emergence and development of these skills. Second, while there is steady growth in network size, there is also substantial variability at any given age during this developmental window. This variability opens up questions about how variation in network size relates to variation in social cognitive skill – these are questions that can be asked in infancy and throughout early childhood.

High and Low Intense Relationships and Age

The proportion of high and low intense relationships were not correlated with child age. There was no evidence that the proportion of high intense relationships ($rho = -0.03$, $p = 0.72$) or proportion of low intense relationships ($rho = 0.03$, $p = 0.72$) was correlated with age (Figure 10).

Proportion of Kin and Adult Relationships and Age

Proportion of kin and proportion of adult relationships were correlated with age. Both proportion of kin relationships ($rho = -0.41$, $p < 0.001$; Figure 11) and proportion of adult relationships ($rho = -0.42$, $p < 0.001$; Figure 12) were negatively correlated with age. As children got older, their networks decreased in the proportion of kin and adult relationships.

While there was a relationship between child age and proportion of kin relationships, there was no evidence that the proportion of high intense relationships was related to child age; this is surprising because the proportion of kin relationships was positively correlated with the proportion of high intense relationships. Taken together, this suggests that kin relationships were not the only source of high intense relationships in early childhood. As children got older, they started to interact with more people outside their family, but these people could still be high intense relationships, such as a teacher or a close friend. It was also true that not all kin relationships were necessarily high intense ones; in this sample approximately 31% of the kin relationships were also low intense relationships. Although children interacted with less family as they got older, they did not lose their high intense relationships.

Network Racial Diversity and Age

Before exploring how network racial diversity changed with age, Network Racial Entropy and Racial EI Index were correlated with each other using Spearman correlation because both variables are not normally distributed. Figure 13 shows that these two measures of racial diversity were highly correlated with each other (*rho* = 0.72, p <0.001).

There was a significant positive correlation with age for Network Racial Entropy (*rho* = 0.25, p <0.001) and for Network Racial EI Index (*rho* = 0.16, p = 0.01). As children got older the representation of different racial groups in their network increased, as did the racial diversity of the network relative to the child's own race (Figure 14).

Network Linguistic Diversity and Age

Similar to the Network Racial Diversity measures, Network Language Entropy and Linguistic EI Index were correlated with each other before seeing how they correlated with age; results showed that both measures of Network Language Diversity were positively correlated with each other (*rho* = 0.50, p < 0.001; Figure 15).

There was no significant correlation between Network Language Entropy and child age (*rho* = -0.07, p = 0.29) nor between Network Linguistic EI Index and child age (*rho* = 0.09, p = 0.28). Unlike Network Racial Diversity, there was no evidence that Network Language Diversity changed as children got older (Figure 16).

Density and Age

We explored how density changed as preschool-aged children got older. There was no evidence that density and age were related to each other. There was no evidence to suggest that as children got older their networks become less connected (*rho* = -0.19, p = 0.12; Figure 17). Importantly, density could only be calculated for the museum subjects, which was a smaller age range than the rest of our sample. It is possible the null result is due to the constricted age range.

Components and Component Ratio and Age

To explore how network structure related to age, we next looked to see how the number of components and the Component Ratio correlated with age. The number of components was positively correlated with age – as children got older the number of components in their network increased (*rho* = 0.63, $p < 0.001$; Figure 18). Interestingly, the Component Ratio was not correlated with age; there was no evidence that the fragmentation of children's networks varied with age (*rho* = 0.04, $p = 0.59$; Figure 18). It is possible the Component Ratio stayed relatively flat throughout the first few years of development because while it was true that the number of components increased over developmental time, so did network size. The Component Ratio was calculated with Network Size in the denominator (Number of Components – 1 / Network Size – 1), which explains why the relative fragmentation stayed consistent throughout the first few years of life when both the components and network size were rapidly growing. The spike in the graph before children's second birthday were networks that had more than one component, but network sizes less than 10 people.

Summary of Age Findings

Our results showed compelling evidence that as children got older, their network size increased. As children got older the number of people they interacted with on a weekly basis also increased. At a time when children's social cognitive skills are rapidly emerging and developing, they are also experiencing drastic changes to their social world. In addition to an increase in the number of people children saw on a weekly basis, there was a decrease in the proportion of kin and proportion of adult relationships. As children got older, they interacted with more people outside of their immediate family and started to interact with more children and peers. Not only did the number of people who children interacted with changed as they got older, the kinds of people they interacted with changed as well. This raises interesting questions about the role that non-kin and other similar-aged peers play in children's development. Prior developmental work has put huge emphasis on the role of parent-child interactions for early development; however, the results presented here showed that children interacted with several different kinds of people outside the immediate and extended family. It is fruitful to consider the value of these other relationships for children's cognitive development.

In addition to increased network size with child age, there was also evidence that network racial diversity increased with age. The representation of different racial groups in their network and how diverse the network was relative to the child's own race, increased with child age. Interestingly, there was no evidence that network language diversity was related to age; neither language entropy nor the linguistic EI index were correlated with child age. These set of findings have implications for how developmental psychologists should consider the effects of diversity on children's emerging social cognitive abilities. Data from US children suggest that as they get older they are exposed to more racial groups, but they are not necessarily exposed to more different-language speakers.

How Do Social Networks Vary with Daycare or School Experience?

The age analyses showed clear patterns of results about the aspects of early social experience that did and did not vary across developmental time. However, another aspect of early social experience that happens to children in the first few years of life is whether they experience out-of-home childcare – either through daycare or preschool. There is a rich literature that has documented the effects that school has on cognition (Ceci, 1991). However, school and out-of-home childcare also correlates with other aspects of early social experience – children get the opportunity to interact with members outside their immediate family and they have the opportunity to interact with members of different social groups, such as people of different races and people who speak other languages. In the sample, 167 subjects had out-of-home childcare either through school or daycare (M_{age} = 37.8 months, SD_{age} = 14.8 months) and 112 subjects (M_{age} = 26.3 months, SD_{age} = 11.8 months) did not have out-of-home childcare. This allowed us to explore how the network variables changed as a function of childcare experience. For this sample, children who attended school or daycare were significantly older than children who did not attend school or daycare ($t(269) = 7.2$, $p < 0.001$); therefore, age was included as a control variable in the subsequent analysis. This allowed us to ask which aspects of social experience varied as a function of childcare experience, age, or both. For the rest of this paper, out-of-home childcare refers to children who were either in daycare or attended preschool.

The tolerance was calculated for each model to determine the extent that the variables – age and school – could vary independently from each other. The t-tests reported are Wilcoxon Rank Sums.

Out-of-Home Childcare, Age, and Network Size

A linear regression was conducted to test the effects of Age and Out-of-home childcare on Network Size and the regression was significant ($R^2 = 0.39$, $F(3, 275) = 61.3$, $p < 0.001$; Figure 19). Consistent with the previous finding, there was a main effect of age ($\beta = 0.02$, $p < 0.001$), but no main effect of Out-of-home childcare ($\beta = 0.10$, $p = 0.62$), and no significant interaction ($\beta = 0.006$, $p = 0.28$). The tolerance was assessed for this analysis because Age and Out-of-home childcare are related to each other; the tolerance is 0.85 for each variable, which means that Age and Out-of-home childcare can vary 85% independently from each other. Although it is true that children in out-of-home childcare had larger social networks than children without out-of-home childcare ($M_{OutofHomeChildcare}$ = 13 people (5), $M_{NoOutofHomeChildcare}$ = 9 people (5); $W = 5031$, $p < 0.001$), when controlling for the effect of Out-of-home childcare on Network Size, child age was the significant predictor.

Post-hoc, Bonferroni corrected correlations were performed to explore if the age trend is present for both children with and without out-of-home childcare. For both groups of children, there was a significant, positive correlation with age (Out-of-home childcare: $r = 0.61$, $p < 0.001$; No Out-of-home childcare: $r = 0.41$, $p < 0.001$). Regardless of childcare experience, as children got older their networks got larger. Notably, this relationship was weaker for children without out-of-home childcare.

Out-of-Home Childcare, Age, and Proportion High Intense Relationships

A linear regression was conducted to test the effects of Age and Out-of-home childcare on the Proportion of High Intense Relationships. The regression revealed null results ($R^2 = 0.02$, $F(3, 169) = 2.01$, $p = 0.11$); there was no main effect of Age ($\beta = -0.0002$, $p = 0.93$) or Out-of-home childcare ($\beta = 0.003$, $p = 0.97$) and the interaction was not significant ($\beta = -0.003$, $p = 0.44$; Figure 20). There was no evidence that either child age or childcare experience was related to the proportion of high intense relationships in the network.

Out-of-Home Childcare, Age, and Proportion Kin Relationships

Another linear regression was conducted to test the effects of Age and Out-of-home childcare on the Proportion of Kin Relationships and the regression was significant ($R^2 = 0.30$, $F(3, 274) = 41.5$, $p < 0.001$). Consistent with the prior finding, there was a negative, significant effect of Age ($\beta = -0.007$, $p = 0.001$). There was also a negative, significant effect of Out-of-home childcare ($\beta = -0.32$, $p < 0.001$) and no significant interaction ($\beta = 0.002$, $p = 0.44$; Figure 21). As children got older, the Proportion of Kin relationships decreased and children with out-of-home childcare had less proportional kin relationships in their networks.

Out-of-Home Childcare, Age, and Proportion Adult Relationships

Another linear regression was conducted to test the effects of Age and Out-of-home childcare on the Proportion of Adult Relationships and the regression was significant ($R^2 = 0.18$, $F(3, 270) = 21.5$, $p < 0.001$). There was a significant, negative effect of Age ($\beta = -0.004$, $p < 0.005$), but no significant effect of Out-of-home childcare ($\beta = 0.07$, $p = 0.18$), and the interaction was not significant ($\beta = -0.002$, $p = 0.15$; Figure 22). The tolerance was 0.85 for both Age and Out-of-home childcare. Results indicated that as children got older, the proportion of adult relationships in their networks decreased.

Out-of-Home Childcare, Age, and Network Racial Diversity

Two linear regressions were conducted to test the effects of Age and Out-of-home childcare on Network Racial Entropy and Network Racial EI Index. The regression with Network Racial Entropy as the dependent variable was significant ($R^2 = 0.14$, $F(3, 265) = 15.6$, $p < 0.001$). There was no significant effect of Age ($\beta = 0.008$, $p = 0.10$), a significant effect of Out-of-home childcare ($\beta = 0.40$, $p = 0.03$), and the interaction was not significant ($\beta = -0.001$, $p = 0.84$; Figure 23). The previous finding that child age was correlated with Network Racial Entropy seemed to be masking an effect for childcare experience. While there was no evidence that as children got older their networks got more diverse, children with out-of-home childcare had higher Network Racial Entropy than children without out-of-home childcare ($M_{OutofHomeChildcare} = 1.10$, $SD_{OutofHomeChildcare} = 0.56$; $M_{NoOutofHomeChildcare} = 0.64$, $SD_{NoOutofHomeChildcare} = 0.61$).

The next regression tested for an effect of Age and Out-of-home childcare on Network Racial EI Index. The regression was not significant ($R^2 = -0.001$, $F(3, 249) = 0.85$, $p = 0.47$);

there was no effect for Age (β = -0.002, p = 0.70), Out-of-home childcare (β = 0.04, p = 0.81), and the interaction was not significant (β = 0.002, p = 0.68; Figure 23).

Out-of-Home Childcare, Age, and Network Linguistic Diversity

Two linear regressions were conducted to test the effects of Age and Out-of-home childcare on Network Language Entropy and Network Linguistic EI Index. The regression with Network Language Entropy as the dependent variable was not significant (R^2 = -0.003, $F(3, 167)$ = 0.81, p = 0.49). There was no significant effect of Age (β = 0.002, p = 0.84), a significant effect of Out-of-home childcare (β = -0.007, p = 0.98), and the interaction was not significant (β = 0.004, p = 0.66; Figure 24). The next regression tested for an effect of Age and Out-of-home childcare on Network Linguistic EI Index. The regression was not significant (R^2 = -0.006, $F(3, 210)$ = 1.43, p = 0.23); there was no effect for Age (β = -0.005, p = 0.10), Out-of-home childcare (β = 0.20, p = 0.05), and the interaction (β = -0.006, p = 0.08; Figure 24). There was no evidence that either Network Language Diversity measures changed systematically with age or by childcare experience.

Out-of-Home Childcare, Age, and Density

The next analysis looked to see how density changed across Age and Out-of-home childcare experience. A linear regression was conducted to test the effects of Age and Out-of-home childcare on Density and the regression was significant (R^2 = 0.23, $F(3, 89)$ = 9.94, $p <$ 0.001), but revealed null results. There was no effect of Age (β = -0.001, p = 0.87), Out-of-home childcare (β = -0.16, p = 0.67), and the interaction was not significant (β = -0.002, p = 0.77; Figure 25). Although the regression revealed null results, post-hoc Wilcox sum tests revealed that children with out-of-home childcare had lower density scores than children without out-of-home childcare ($M_{OutofHomeChildcare}$ = 0.51, $SD_{OutofHomeChildcare}$ = 0.18; $M_{NoOutofHomeChildcare}$ = 0.79,

$SD_{NoOutofHomeChildcare} = 0.22$; $W = 1023$, $p < 0.001$). Children without out-of-home childcare had more connected networks than children with out-of-home childcare.

Out-of-Home Childcare, Age, and Component Ratio

The next set of analyses looked to see how network structures changed across Age and Out-of-home childcare. First, we explored how the network fragmentation changed across age and childcare experience. A linear regression was conducted to test the effects of Age and Out-of-home childcare on the Component Ratio. The regression was significant ($R^2 = 0.06$, $F(3, 266) = 6.36$, $p < 0.001$). There was no significant effect of Age ($\beta = 0.0002$, $p = 0.86$) and the interaction was not significant ($\beta = -0.001$, $p = 0.21$), but there was a significant effect of Out-of-home childcare ($\beta = 0.10$, $p = 0.004$). Children in school or daycare had more fragmented networks than children not in school or daycare (Figure 26).

Summary of Age and Out-of-Home Childcare Findings

Our results highlighted some aspects of early social experience that seemed to be shaped by childcare experience and age. While it is true that children with out-of-home childcare had larger social networks than children without out-of-home childcare, across childcare experience children experienced growth in their network size as they got older. This was confirmed by the linear regression and post-hoc correlations. Proportion of kin and proportion of adult relationships also varied by age – there were decreases to both as children got older. Across childcare experience, children interacted with more people as they got older. At a time when children's skills are rapidly developing – they are seeing increases in their theory of mind skill, they are improving their communication skills, they are updating and redefining their conceptions of people from different social groups – they are also seeing increases in the number of people they interact with.

While children saw growth in their network size across developmental time, there was also evidence that some aspects of early social experience seemed to be related to childcare experience. The representation of different racial groups was impacted by childcare experience – children with out-of-home childcare had greater racial entropy than children without out-of-home childcare. Further, childcare experience had a dramatic impact on the structure of children's networks – children with out-of-home childcare had more fragmented networks and they had less connected networks. Describing and understanding the structure and pattern of relationships has important implications for thinking about how out-groups members are patterned in the network. Does it matter if out-group members are interconnected or more dispersed? Describing and exploring network structure will allow developmental psychologists to better understand the ways that contact with out-groups members affects cognition.

How Do Network and Neighborhood Diversity Relate to Each Other?

The final set of analyses explored how network and neighborhood diversity measures, specifically racial and linguistic diversity, related to each other. Prior developmental work has used neighborhood demographics to approximate experience (Mandalaywala et al., 2019; Weisman et al., 2015), but only one study has used neighborhood demographics to test how distal social experience affects cognition (Howard et al., 2014). It remains an open question whether neighborhood demographics correlate with the demographics of children's close relationships. Using children's social network data and the US Census data, we can explore this possibility. Participants provided their zip code and their neighborhood racial and language entropy could be calculated using the American Community Census Survey from 2018.

Network and Neighborhood Racial Diversity

Network and Neighborhood Racial Entropy were correlated with each other and results showed that Network and Neighborhood Racial Entropy were positively correlated with each other (*rho* = 0.17, $p < 0.005$; Figure 27). We further explored whether this varied by the geographic location – either urban or suburban and rural areas. Using the zip code, each participant was classified as either living in an urban area or suburban area according to the CDC's classification of counties (Ingram & Franco, 2014). For the participants who lived in Cook county, but not in Chicago, IL, were classified as living in a suburban area. In our sample, 183 subjects lived in an urban area and 90 subjects lived in a suburban or rural area. Figure 28 shows Network and Neighborhood Racial Entropy by urban and suburban/rural areas. Spearman correlations revealed that for urban subjects only, there was a positive correlation between Network and Neighborhood Racial Diversity (*rho* = 0.24, $p = 0.002$). There was no evidence that Network and Neighborhood Racial Diversity were correlated for suburban or rural subjects (*rho* = 0.02, $p = 0.89$).

Network and Neighborhood Language Diversity

Network and Neighborhood Language Diversity were correlated with each other and results showed that, similar to the Racial Diversity findings, Network and Neighborhood Language Entropy were positively correlated with each other (*rho* = 0.22, $p = 0.004$; Figure 29). The geographic analysis showed the same pattern of results as the Racial Diversity findings. There was no evidence that Network and Neighborhood Language Entropy were related in suburban and rural areas (*rho* = 0.07, $p = 0.71$), but there was a positive correlation for urban areas (*rho* = 0.25, $p = 0.004$; Figure 30).

Summary of Neighborhood Findings

For both Racial and Language Diversity, network and neighborhood entropy were correlated with each other; however, this finding seemed to be driven by the subjects living in urban areas. For subjects living in suburban and rural areas, there was no evidence that their network and neighborhood Racial and Language Diversity were correlated. It is possible there was no evidence that network and neighborhood demographics map onto each other for suburban and rural areas because these areas are not as densely populated. Even if a suburban area has higher levels of Neighborhood Racial Entropy, that diversity could be spread out across greater areas of land than in urban areas. Most of the urban sample is from Chicago, IL, which is a densely populated city and it is therefore reasonable that children's close relationships would match the demographics of their community. Future work can explore why network and neighborhood demographics do or do not map onto each other; it is possible this effect could be explained by parents' values about community involvement or the extent that their own social networks reflect the demographics of the communities that they live in. Although there are several open questions, this initial analysis highlights the problems with using neighborhood demographics to approximate typical experience; depending on the area where a child lives, these different aspects of experience do not necessarily map onto each other.

Discussion

This paper has demonstrated that the tools of social network analysis can be used in developmental science to capture and describe children's early social environments. The tools of social network analysis are not only helpful to describe early social environments, but once early social experience is conceptualized as network properties, Social Network Theory can be used as a framework to generate hypotheses about how early social experience impacts cognition and development (e.g., Does the number of individuals a child interacts with on a weekly basis impact their social cognitive skills?). The data presented in this paper provide an initial look at how social network analysis can be used in developmental science and raises several interesting implications for studying and understanding children's early social environments.

Children's social network data illustrate the varied aspects of social network structure that can be identified in infancy and early childhood. As the results showed, while several of these network variables and aspects of early social environments are conceptually distinct, they might also be empirically correlated with each other. To best understand how early social environments relate to children's development, it is important to understand the aspects of early social environments that are related to each other. We presented analyses about how aspects of experience were correlated for this particular highly educated, urban sample in the US; however, it is possible, and in fact likely, that different patterns and trends would emerge for different samples of children, both cross-culturally and within the US. Social network analysis is useful for developmental science because dimensions of networks can be used to describe social environments, but it is also useful because it provides a framework to understand the embedded and complex nature of early social environments.

Our results also highlight the ways in which children's social networks change across infancy and early childhood. Most notably, our cross-sectional analysis showed that as child age increased, so did network size. This was true across early development, during infancy and continuing into the preschool years. As children begin to enter daycare and school experiences, these contexts were associated with increased network size, but even among children who did not attend daycare or school, network size increased with age. At a time when core aspects of social cognition are developing, children's social networks are undergoing significant change. This raises the obvious question of whether and how social cognitive development maybe affected by changing social environments, and it raises the possibility that developments that have been assumed to reflect internally timed maturation may instead, or in addition, be driven by experience.

As an example, during the first few years of life, children undergo massive developments to their perspective-taking ability. While the development of skills like perspective-taking could reflect maturation, it is not known how the drastic changes in the social network might impact the development of this skill. Prior work with adults has shown that adults with larger social networks are better at perspective-taking skill (Stiller & Dunbar, 2007), which suggests that this might be true for children as well. It is impossible to determine the causality of a given effect in correlational network research; however, while adults have autonomy in who is included in their social network, children’s social networks reflect parent childcare decisions. Children, particularly infants, have relatively little autonomy in who they interact with on a regular basis, raising the question that perhaps changes in social experience are the drivers of social cognitive change. This would be consistent with research on non-human primates, which demonstrated the size of the social network primates were placed in at birth related to neural substrates of social cognition (Sallet et al., 2011). The CSNQ, in combination with longitudinal research designs, can be used to address this possibility.

While aspects of early social experience change as a function of age, this analysis also highlighted that some aspects of experience are affected by contextual experience, such as attending out-of-home-childcare. Our results showed that children with out-of-home-childcare were exposed to more racial groups than children not in daycare. Additionally, the network structure was largely impacted by childcare experience – children in daycare had both more fragmented networks and networks that were not as connected. Experience with out-of-home-childcare not only affected the kinds of people a child interacted with, but it also impacted *how* those people were connected. Finally, our results highlighted that network and neighborhood racial and linguistic demographics are not always correlated with each other; this demonstrates why it is problematic to use neighborhood demographics to approximate typical experience and pushes against assumptions that characteristics of a neighborhood would be reflected in children's immediate social environments. Future work should be explicit in how experience is characterized and use neighborhood data to talk about more distal social environments.

The data presented here demonstrate the importance of understanding the contextual variation for developmental samples. The results suggest that the social environments for children in different social groups or in different geographic locations might vary in systematic ways. The ways that early social environments might affect children in different social groups or locations might differ dramatically because the structure and composition of their social environments are not the same. When there are observable differences in behavior for children in different social groups, it is fruitful to consider how differences in their network composition and structure might be affecting those patterns.

It is important to reiterate that our sample is highly educated (over 70% of mother's have a bachelor's degree or higher), approximately half White, and mostly reside in or around a large, urban city; it is necessary to test widely to explore whether these findings generalize across different samples. As stated above it is possible, and likely, that these patterns vary across different samples, even within the US. In particular with SES diversity, there are theories in the network literature that suggest adults from high- versus low-SES backgrounds have different functions for the strong and weak ties in their networks (Campbell et al., 1986; Granovetter, 1983; McPherson et al., 2005) and there is recent data to suggest this is true; there is a general trend in the US that adults with higher levels of education have less kin relationships in their social networks (McPherson et al., 2005). Future work will need to explore whether these trajectories of early social experience are the same for children from low-SES backgrounds.

Recommendations for Developmentalists Who Want to Use Social Network Analysis

Developmentalists have nuanced theories about the kind of experiences that might be important for shaping children's early social cognition. However, until now there have not been the proper tools to capture the whole picture of infant and young children's early social interactions. *The Child Social Network Questionnaire* is a powerful tool that can begin to address age old debates as well as cutting age theories about social cognitive development.

To most effectively use network analysis and methods, it is necessary to be intentional about applying social network analysis to developmental questions. Social network analysis is a powerful tool and it is not a method that can be applied thoughtlessly. Social network theory will generate several hypotheses about how early social environments affect social cognition; however, it is crucial to be thoughtful and specify which kinds of experience might matter for development. Social network theory can be used as the framework to consider how certain aspects of experience might be correlated with each other; this framework and school of thought can then lead to thoughtful experimental design to tease apart which kinds of experience might matter for development. Sophisticated data analysis tools and methods cannot save poorly designed social science research (Robins, 2015). Relatedly, it is important to not overinterpret data and to be clear about what claims can and cannot be made from social network research. Early social environments are complex and embedded and social network research is largely correlational; it is necessary to be clear and honest about what conclusions can be drawn from the data when social environments are complex and embedded.

The Child Social Network Questionnaire used social network methods to capture and describe the people children interact with on a regular basis, but children do not have one social network. Social networks are a flexible tool and several different kinds of networks can be extracted for an individual; the network space is determined by the research question (Borgatti & Halgin, 2011). For each of the dimensions of the social networks, a researcher can make different decisions about what kind of network will be examined. For example, instead of asking about who the child interacts with during a typical week, a researcher could ask about every individual the child saw in the last month, which would cast a wider network space of people to be included. The questions that are asked about each of the alters can also vary. The CSNQ focused on racial and linguistic network diversity, but a researcher could ask an endless amount of questions about each of the alters: religious affiliation, political identity, education level, food preferences, or even shared beliefs. Finally, the kind of relationships that are examined could vary. The CSNQ focused on who the child "knew", but the relationships that are examined could be affective ones (who the child "likes" or "dislikes") or even event-based interactions, such as how many times a child plays with another child (Borgatti & Halgin, 2011). *The Child Social Network Questionnaire* made decisions across these three dimensions to make this tool most useful to developmental psychologists; however, network methods can be adjusted to extract different kinds of networks based on the desired research question.

In summary, *The Child Social Network Questionnaire* is an excellent tool to capture and describe children's early social relationships and the network perspective is a useful framework that developmental psychologists can use to explore how experience impacts social cognition. Once early social environments are conceptualized in a unified framework, social network theory can be used as a framework to generate questions and hypotheses about how experience impacts social cognitive development. For example, if the racial diversity matters for children's intergroup cognition, does it matter how that diversity is patterned in the network? Or does racial diversity mask an effect of network size, given that children in networks with high amounts of racial diversity are also in large social networks? A network perspective will expand and explore these kinds of questions, which will allow us to fine tune our theories about how early social experiences impacts social cognition and produce theoretically driven hypotheses about the mechanisms of early social experience.

In addition to expanding our current questions about how experience impacts cognition, this framework can also be used as a lens to understand more nuanced debates. For example, there is a robust literature that illustrates children with siblings show superior theory of mind skills than only-children (see Jenkins & Astington, 1996 and Perner, Ruffman, & Leekam, 1994 for examples); however, although smaller in number, there are several studies that do not find an effect of siblings and theory of mind (Arranz et al., 2002; Carlson & Moses, 2001; Cutting & Dunn, 1999). Social network theory can be used as a lens to understand the mixed literature, by arguing that the focus on siblings was too narrow. Our data demonstrate that children interact with several more people outside of their siblings on a regular basis. Instead of exploring how the number or presence of siblings impacts theory of mind skill, it would be fruitful to consider a wider range of children's social interactions. Prior work that found a correlation between theory of mind skill and the number of siblings, but also the number of friends, suggests this is true (Wright & Mahfoud, 2012).

Studies that want to explore how individual differences in early social environments impact cognition would benefit from using *The Child Social Network Questionnaire* and a network perspective. The data presented here is an important first step for this framework. This paper has demonstrated that social network analysis can be used with infants and young children and it has provided both a tool and framework to better explore how early social environments impact social cognition.

Table 1

Table of the Social Network Variables

	Mean (SD)	range
Network Size	11.0 (5.0)	3 - 27
Raw Number of Low Intense Relationships	3.9 (3.2)	0 - 15
Raw Number of High Intense Relationships	3.8 (2.0)	1 - 12
Proportion of High Intense Relationships	0.54 (0.23)	0.13 - 1.0
Proportion of Kin Relationships	0.52 (0.24)	0.05 - 1.0
Proportion of Adult Relationships	0.65 (0.18)	0.05 - 1.0
Network Structure		
Density	0.56 (0.21)	0.21 - 1.0
Number of Components	2.5 (1.2)	1 - 7
Component Ratio	0.15 (0.12)	0 - 0.67
Diversity Measures		
Racial Entropy	0.91 (0.62)	0 - 2.4
Racial EI Index	-0.51 (0.45)	-1 – 0.8
Language Entropy	0.69 (0.44)	0 – 1.8
Language EI Index	-0.76 (0.29)	-1 – 0.2

Table 2

2x2 Table Showing Kin and Intense Relationships

	High Intense Relationships		Low Intense Relationships	
	n	*% of total*	*n*	*% of total*
Kin Relationships	471	42%	212	19%
Not Kin Relationships	90	8%	349	31%

Table 3

Table of Correlations Between Network Size, Age, and Other Network Variables

	Network Size	Child Age
	Spearman rho	*Spearman rho*
Network Size	-	**0.61*****
Child Age	**0.61*****	-
Prop High Intense Relationships	**-0.41*****	-0.03
Proportion of Kin Relationships	**-0.56*****	**-0.41*****
Proportion of Adult Relationships	**-0.38*****	**-0.42*****
Density	**-0.52*****	-0.19
Number of Components	**0.63*****	**0.63*****
Component Ratio	-0.01	0.04
Racial Entropy	**0.35*****	**0.25****
Racial EI Index	**0.24*****	**0.16***
Language Entropy	-0.01	-0.07
Language EI Index	**0.24*****	0.09

*** $p < 0.001$ **$p < 0.01$ *$p < 0.05$

Table 4

Example Social Network Information

	Network Size	Network Racial Entropy	# of Components	Family Component	School Component	Other Component1	Other Component2
Subject ID							
Sub1	9	1.22	2	0.00	1.5	-	-
Sub2	18	1.22	4	1.25	1.22	1.52	1.56
Sub3	14	1.52	4	1.49	0.81	1.49	0.81
Sub4	10	1.52	2	0.00	1.41	-	-
Sub5	9	0.50	3	0.00	0.92	0.00	-
Sub6	9	0.50	2	0.00	0.65	-	-
Sub7	9	0.50	2	0.00	0.72	-	-

Note. The table highlights examples of subjects that had a similar overall network racial entropy, but the racial diversity patterned differently in the network.

Table 5

Racial/Ethnic Diversity Measures

Measure	Racial Entropy			Racial EI Index		
	M	*SD*	*Range*	*M*	*SD*	*Range*
Racial/Ethnic Category						
African or Black-American	0.60	0.62	0.00 – 1.69	-0.58	0.53	-1.00 – 0.75
Asian or Asian-American	1.04	0.52	0.00 – 1.81	-0.27	0.42	-1.00 – 0.25
Biracial	1.46	0.52	0.50 – 2.41	-0.51	0.50	-1.00 – 0.73
European or White-American	0.84	0.55	0.00 – 2.18	-0.51	0.38	-1.00 – 0.50
Hispanic or Latino-American	0.60	0.61	0.00 – 1.85	-0.53	0.60	-1.00 – 0.8
Other	0.53	0.74	0.00 – 1.05	-0.73	0.38	-1.00 - -0.47

Note. This table shows the racial diversity measures for each racial/ethnic subgroup in our sample.

Table 6

Table of Network Variables by Racial Majority vs. Racial Minority Children

	Racial Majority (White)	Racial Minority
	M(SD)	*M(SD)*
Network Size	11.9 people (5.8)	10.6 people (4.7)
Proportion of High Intense Relationships	0.52 (0.23)	0.57 (0.23)
Proportion of Kin Relationships	**0.48 (0.22)**	**0.57 (0.27)***
Proportion of Adult Relationships	0.65 (0.17)	0.66 (0.18)
Network Structure		
Number of Components	**2.68 (1.21)**	**2.35 (1.19)***
Component Ratio	**0.16 (0.11)**	**0.14 (0.13)***
Density	0.56 (0.23)	0.57 (0.20)
Diversity Measures		
Racial Entropy	0.84 (0.55)	1.01 (0.69)
Racial EI Index	-0.51 (0.38)	-0.51 (0.52)
Complexity (museum subjects only)		
Proportion of Zero Entropy Components	0.36 (0.26)	0.26 (0.33)
Percentage of children with Integrated Networks	52%	64%
Percentage of children with Segregated Networks	44%	28%
Percentage of children with no diversity networks	4%	8%
Friendship Analysis (entire sample)		
Number of Friends	2.0 (2.2)	1.4 (1.8)
Friendship Racial Entropy	0.52 (0.59)	0.48 (0.53)
Friendship Racial EI Index	-0.35 (0.69)	-0.31 (0.77)

*$p < 0.05$

Table 7

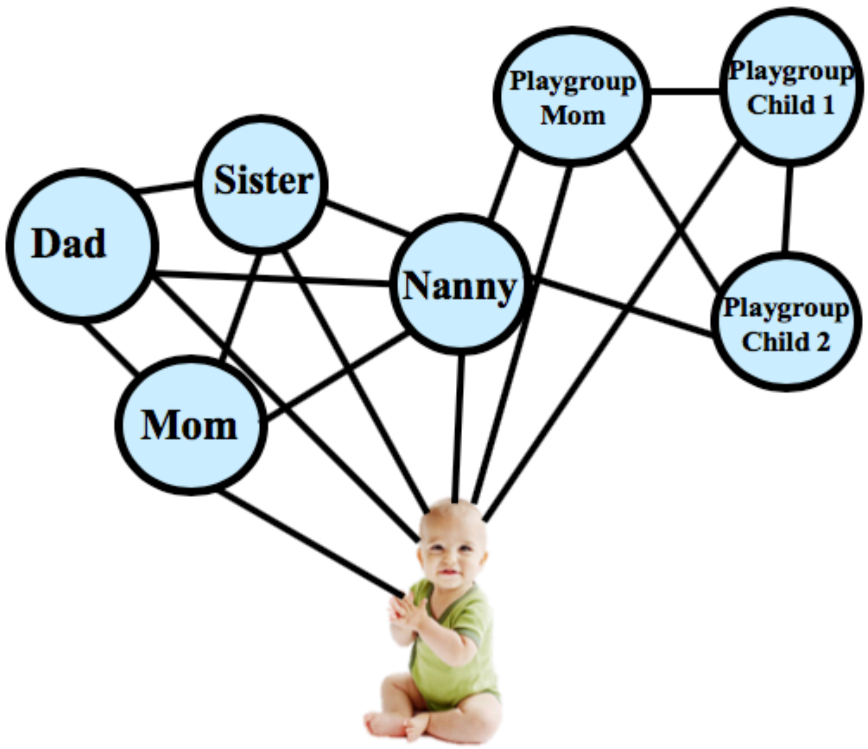
Table of Network Variables by Monolinguals vs. Multilingual Speakers

	Monolingual English Speakers	Multilingual Speakers
	M(SD)	*M(SD)*
Network Size	11.8 people (5.6)	11.0 people (5.1)
Proportion of High Intense Relationships	0.54 (0.24)	0.53 (0.22)
Proportion of Kin Relationships	0.50 (0.24)	0.52 (0.24)
Proportion of Adult Relationships	0.64 (0.16)	0.66 (0.19)
Network Structure		
Number of Components	2.69 (1.20)	2.44 (1.22)
Component Ratio	0.16 (0.11)	0.15 (0.12)
Density	0.54 (0.22)	0.59 (0.20)
Diversity Measures		
Language Entropy	**0.48 (0.39)**	**0.96 (0.34)***
Linguistic EI Index	**-0.74 (0.29)**	**-0.81 (0.30)***
Friendship Analysis		
Number of Friends	1.9 (2.1)	1.7 (2.0)
Friendship Language Entropy	0.17 (0.36)	0.28 (0.44)
Friendship Linguistic EI Index	**-0.11 (0.97)**	**0.46 (0.78)****

** $p < 0.001$ *$p < 0.05$

Figure 1

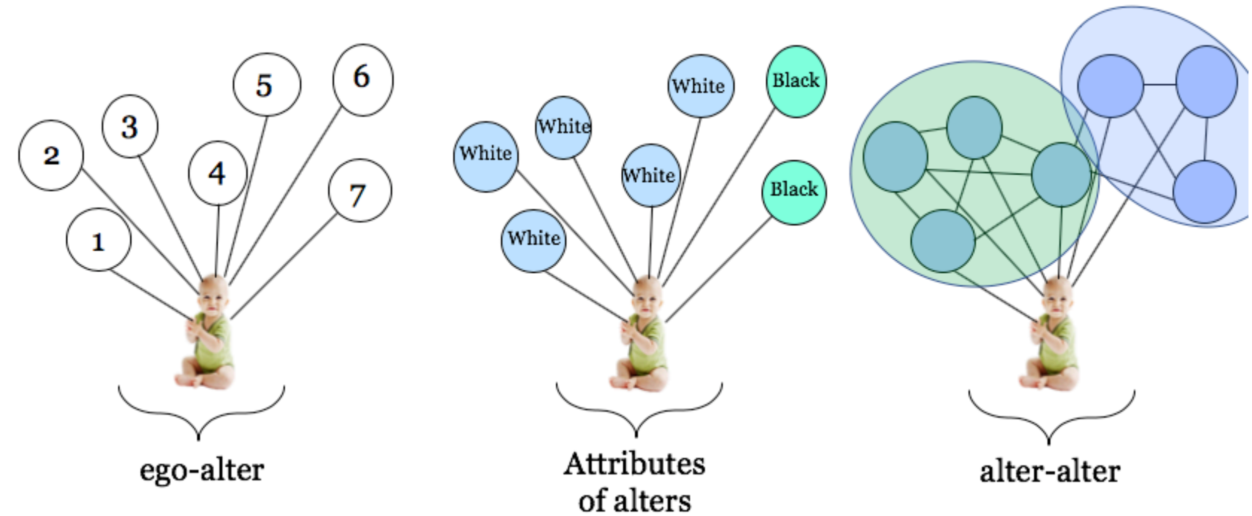
A Child and Their Social Network



Note. The blue circles represent different people. These people are called “nodes” or “alters”.

Figure 2

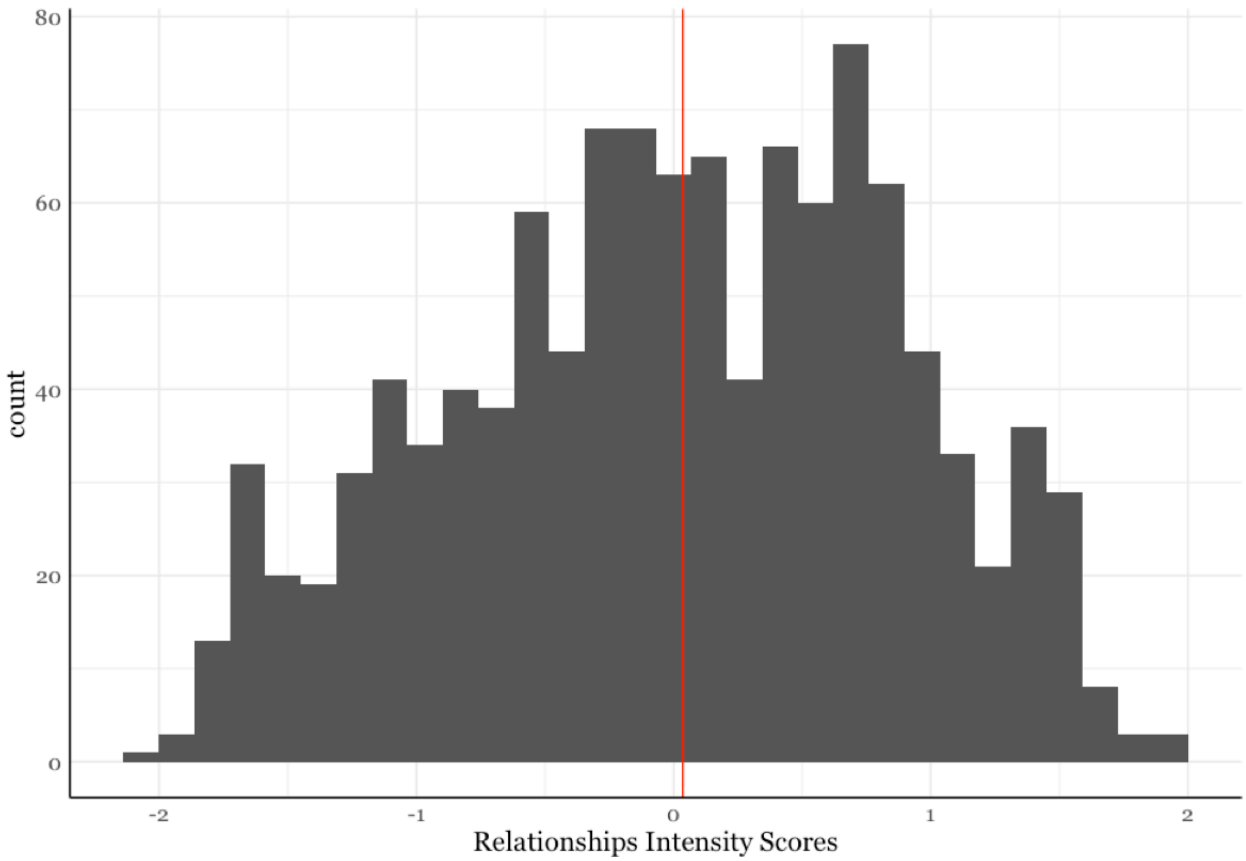
3 Dimensions of a Social Network



Note. The 3 dimensions to describe a social network are the relationships between alters and child (ego-alter), the attributes of alters, and the relationships between the alters (Perry et al., 2018).

Figure 3

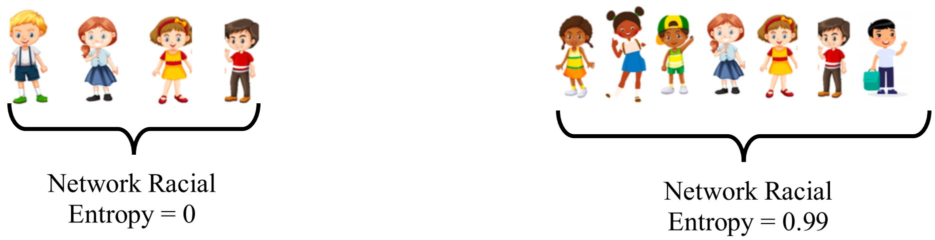
Histogram of The Relationship Intensity Z-Scores



Note. The red line represents the median used to classify relationships as either “low” or “high” intense.

Figure 4

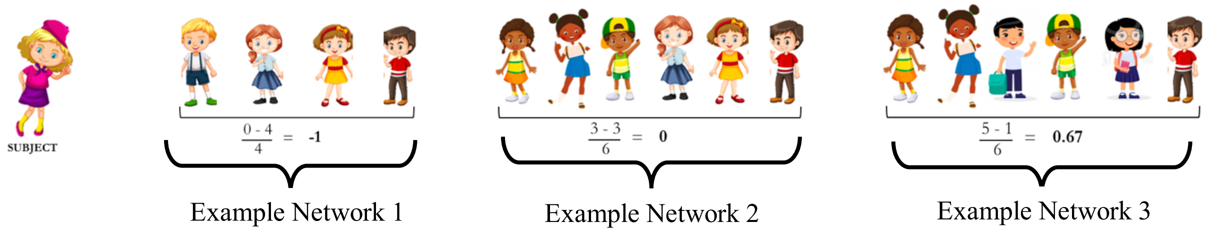
Example Network Racial Entropy Values



Note. Above are examples networks and their corresponding Network Racial Entropy score. A score of 0 indicates that there is no racial diversity; all the people in the network are the same race.

Figure 5

Example Racial EI Index Values



Note. The pictures above show what the Racial EI Index would be if the child was White. A score of -1 means the entire network is the same race as the child.

Figure 6

Example Network Graphs

Density = 0.21, Network Size = 26 Density = 1.0, Network Size = 14

Note. The blue circles represent a child or “ego”. The lower the value, the less connected the social network.

Figure 7

Histogram of Proportion of Zero Entropy Components

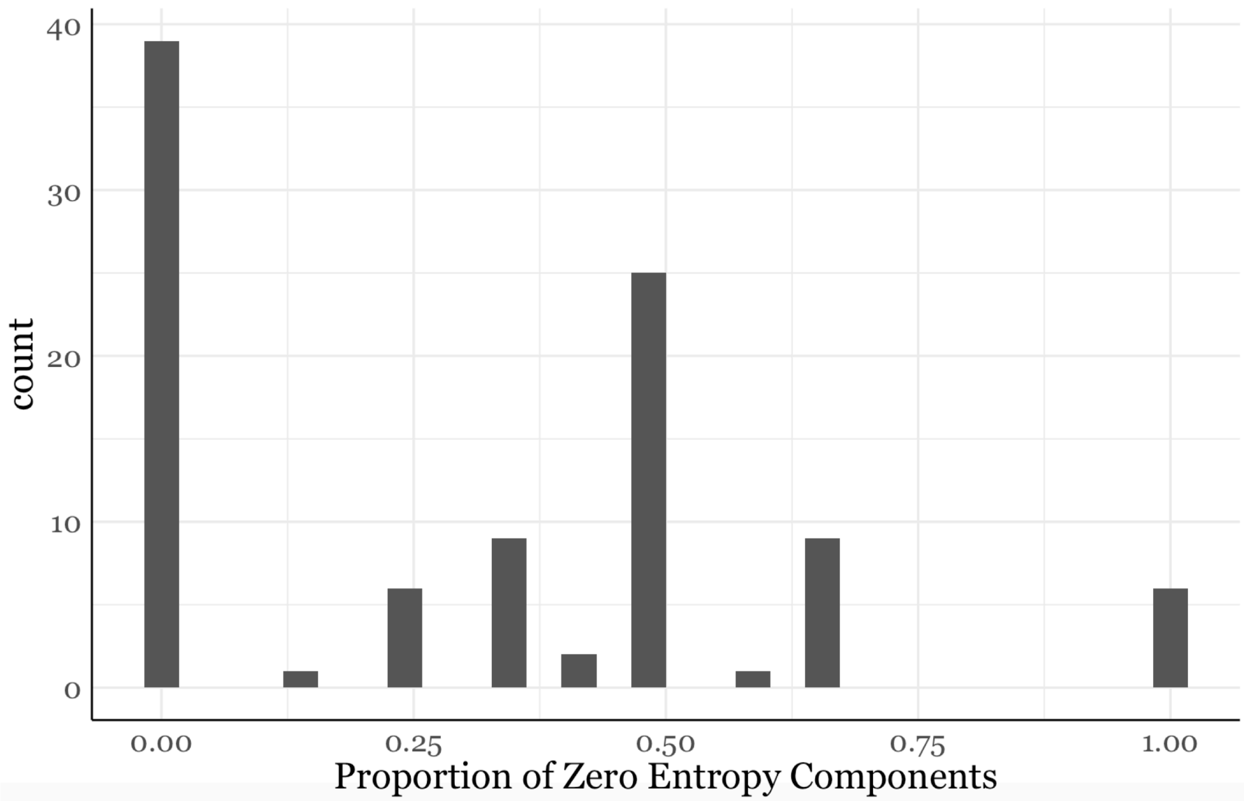
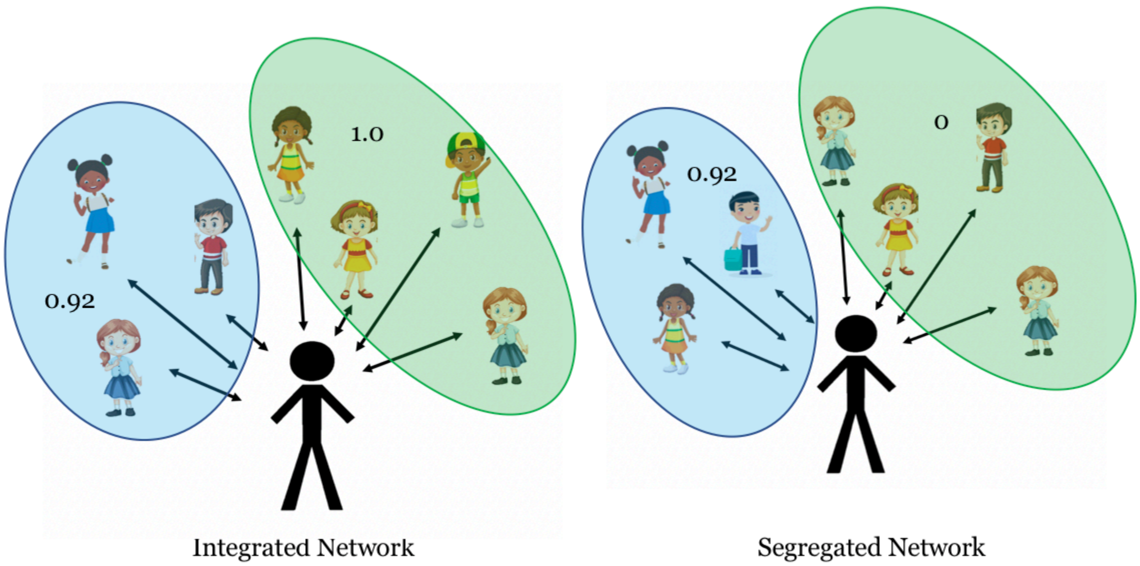


Figure 8

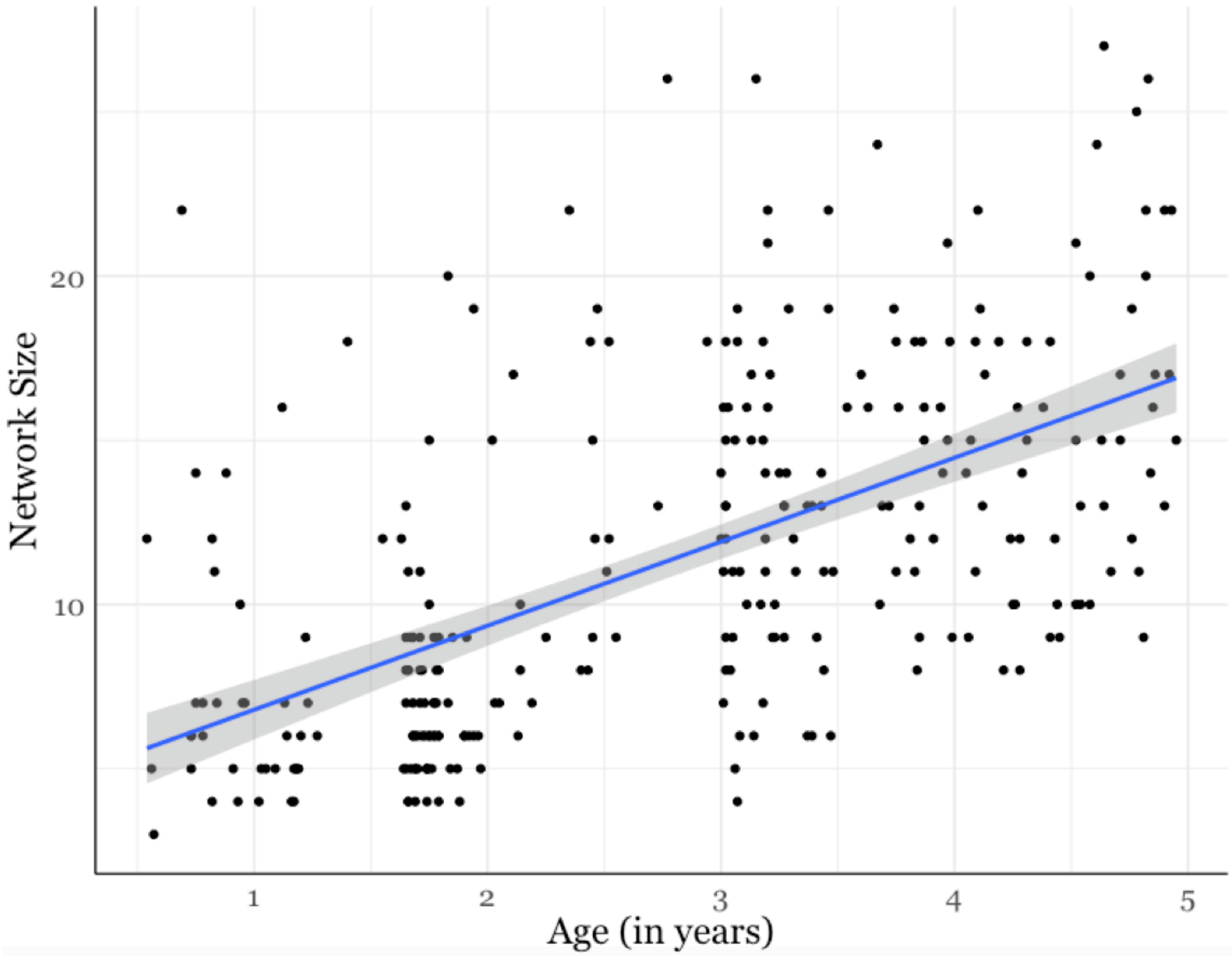
Examples of Integrated and Segregated Networks



Note. The Integrated Network has 2 components that have non-zero entropy in each component – there are different racial groups represented in each component. The Segregated Network shows that 50% of the components have 0 racial entropy.

Figure 9

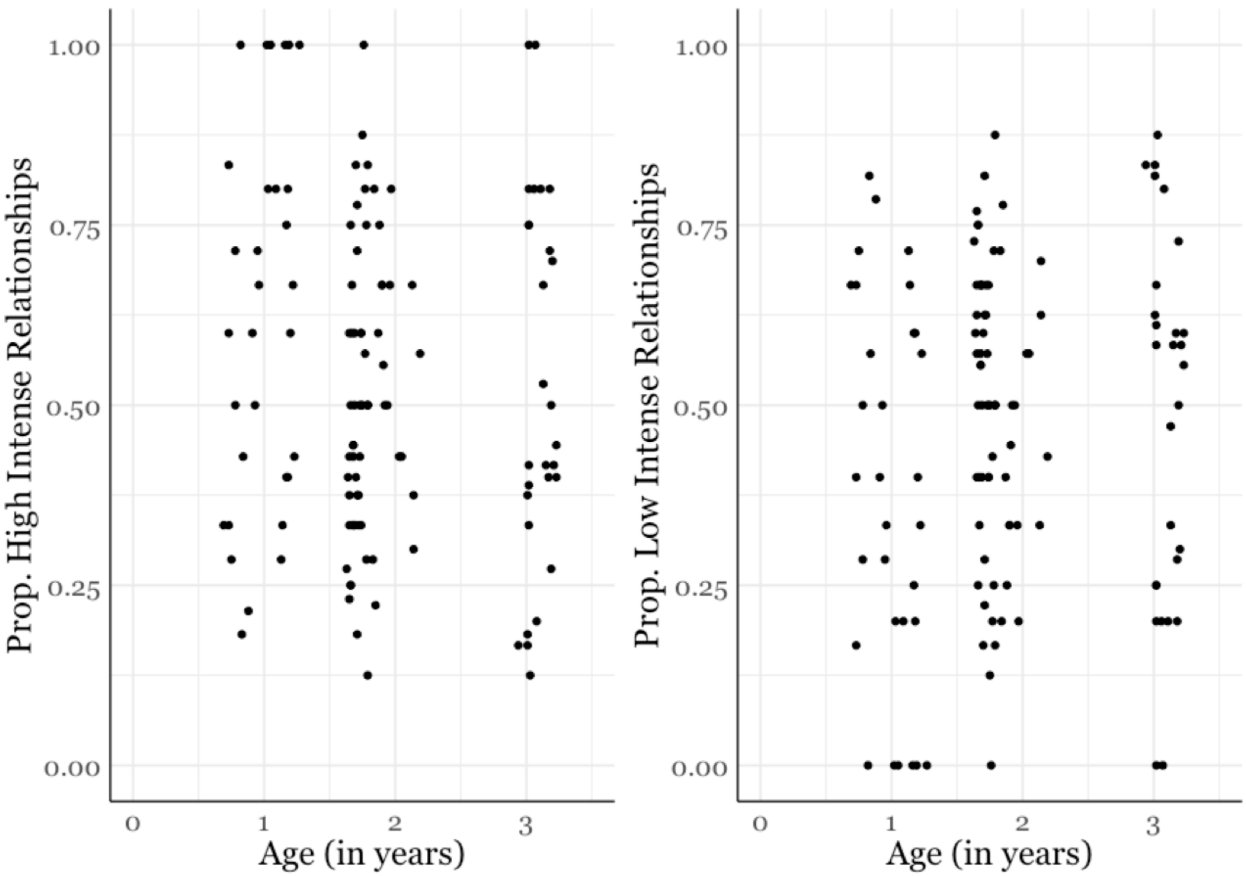
Network Size Increased with Age



Note. The results showed a significant, positive correlation between Network Size and child age; as children got older their Network Size increased ($r = 0.61$, $p < 0.001$).

Figure 10

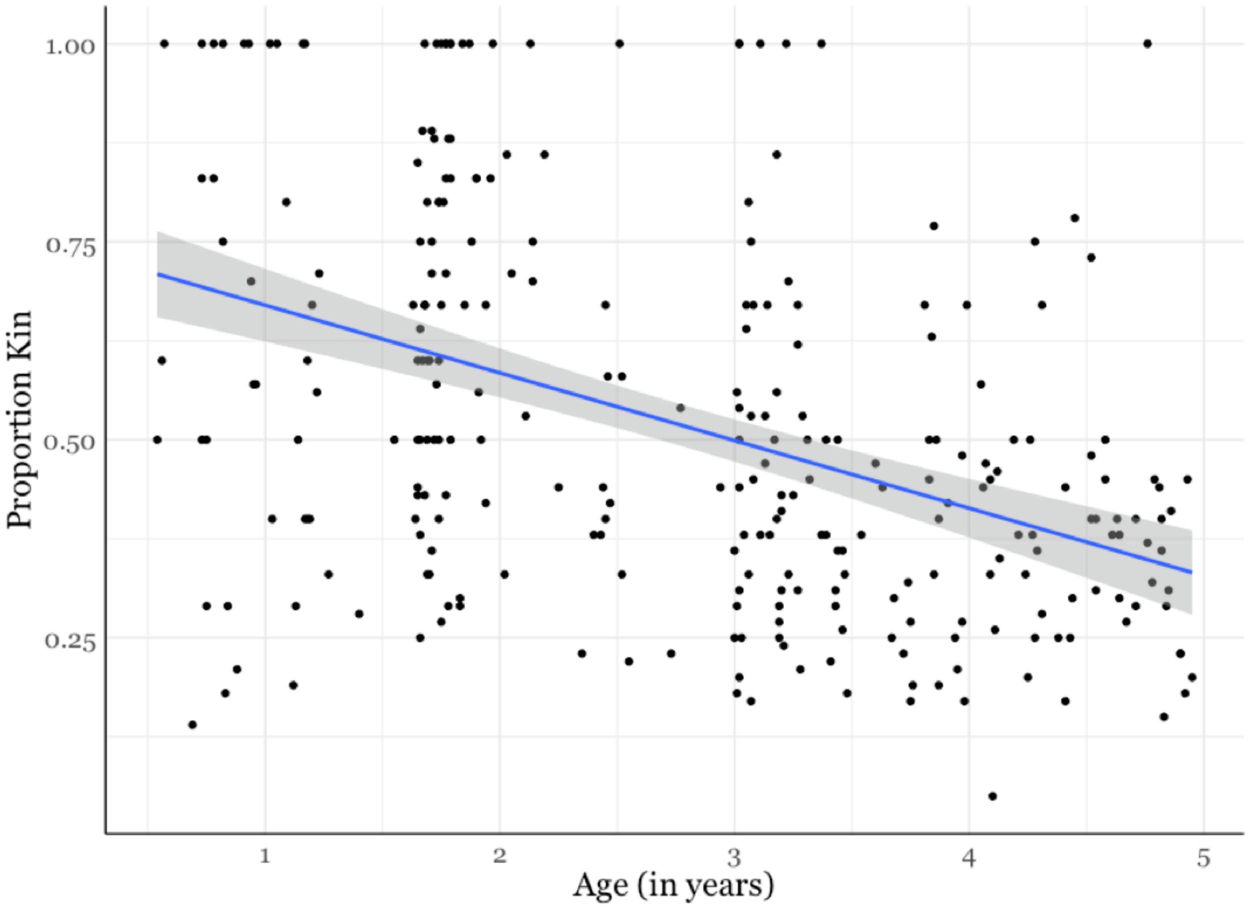
Proportion of High and Low Intense Relationships with Age



Note. There was no evidence that the proportion of high intense relationships (*rho* = -0.03, *p* = 0.72) or proportion of low intense relationships (*rho* = 0.03, *p* = 0.72) were correlated with age.

Figure 11

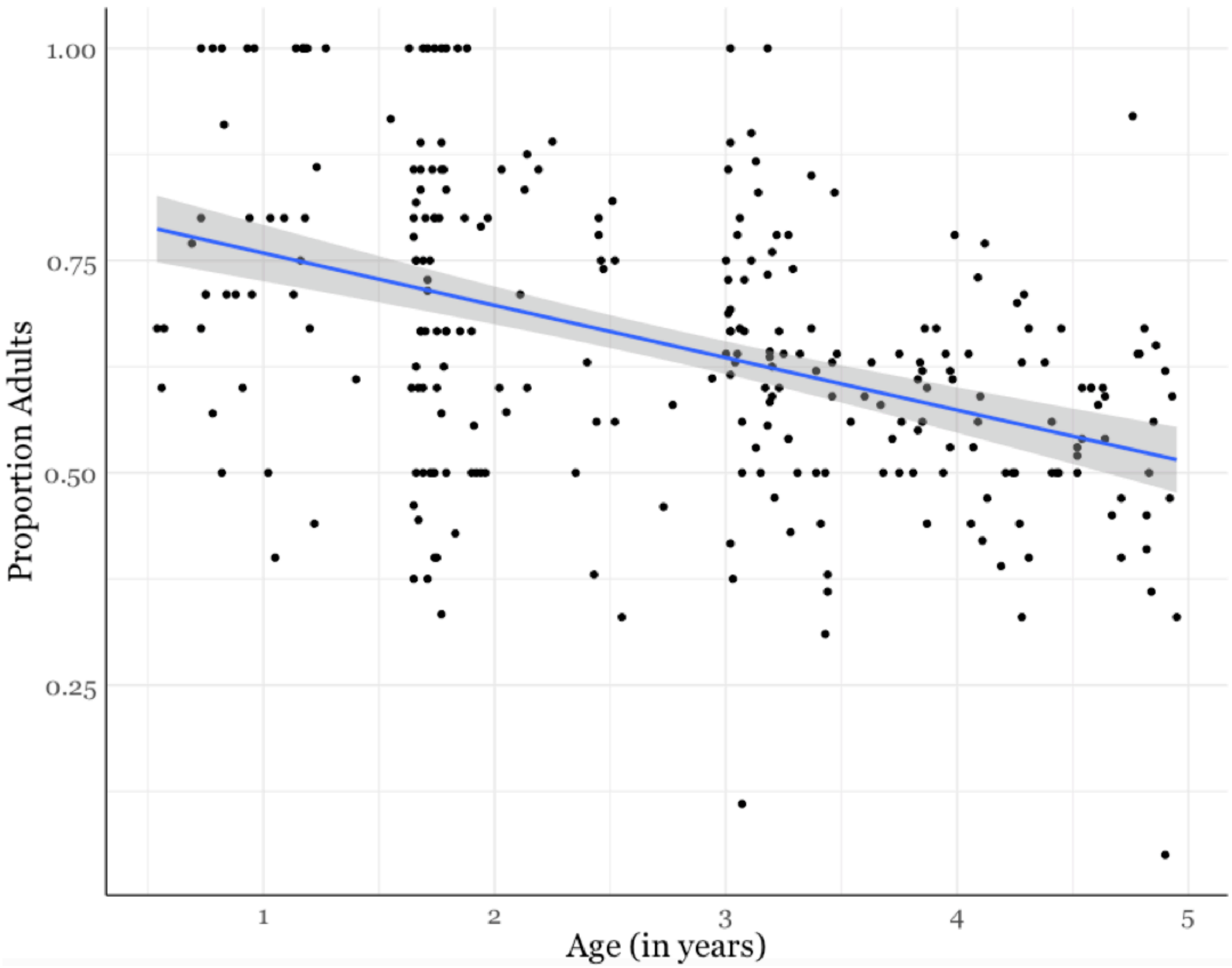
Proportion of Kin Relationships with Age



Note. Proportion of kin was correlated with child age (*rho* = -0.41, $p < 0.001$).

Figure 12

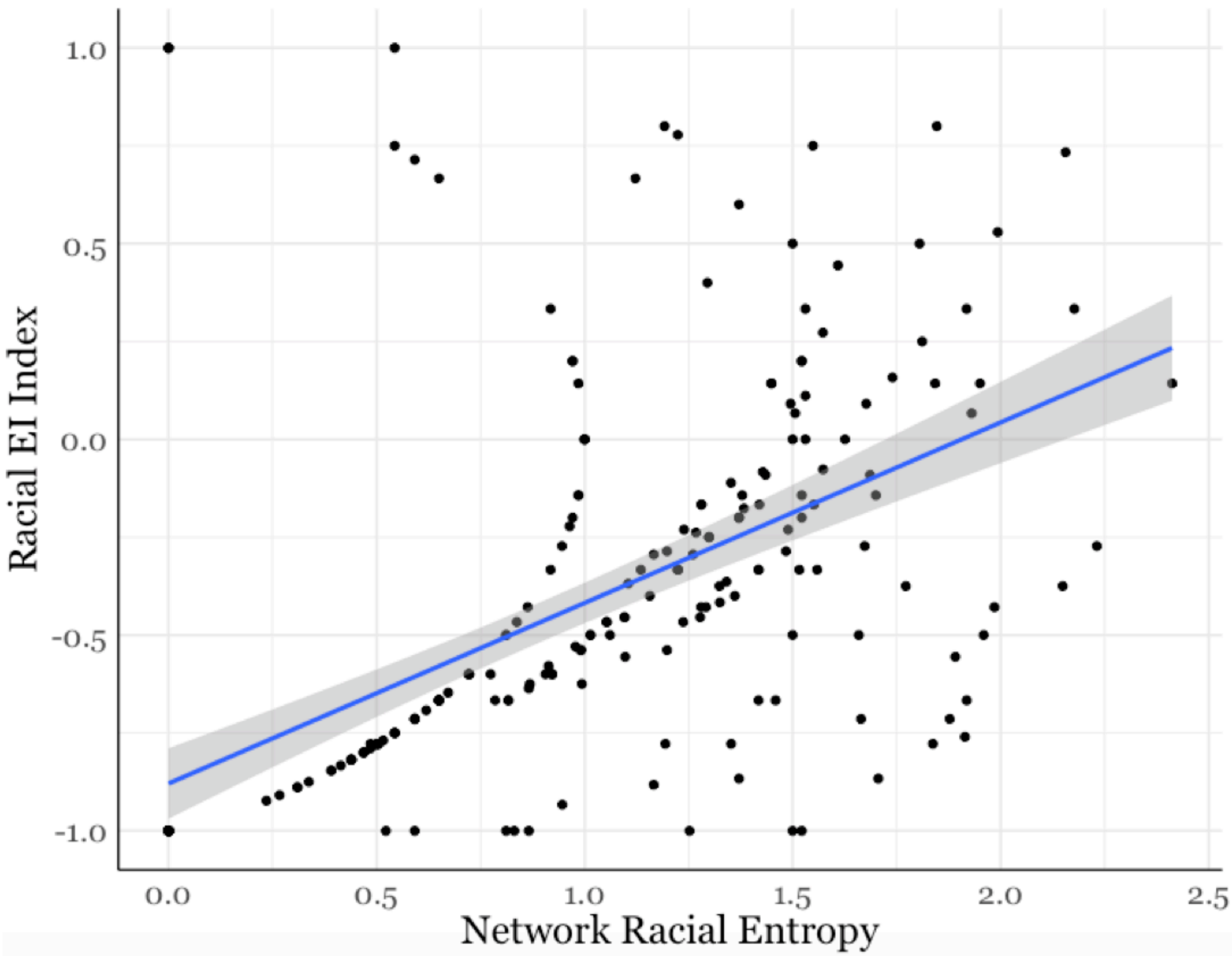
Proportion of Adult Relationships with Age



Note. Proportion of adult relationships was correlated with child age (*rho* = -0.42, $p < 0.001$).

Figure 13

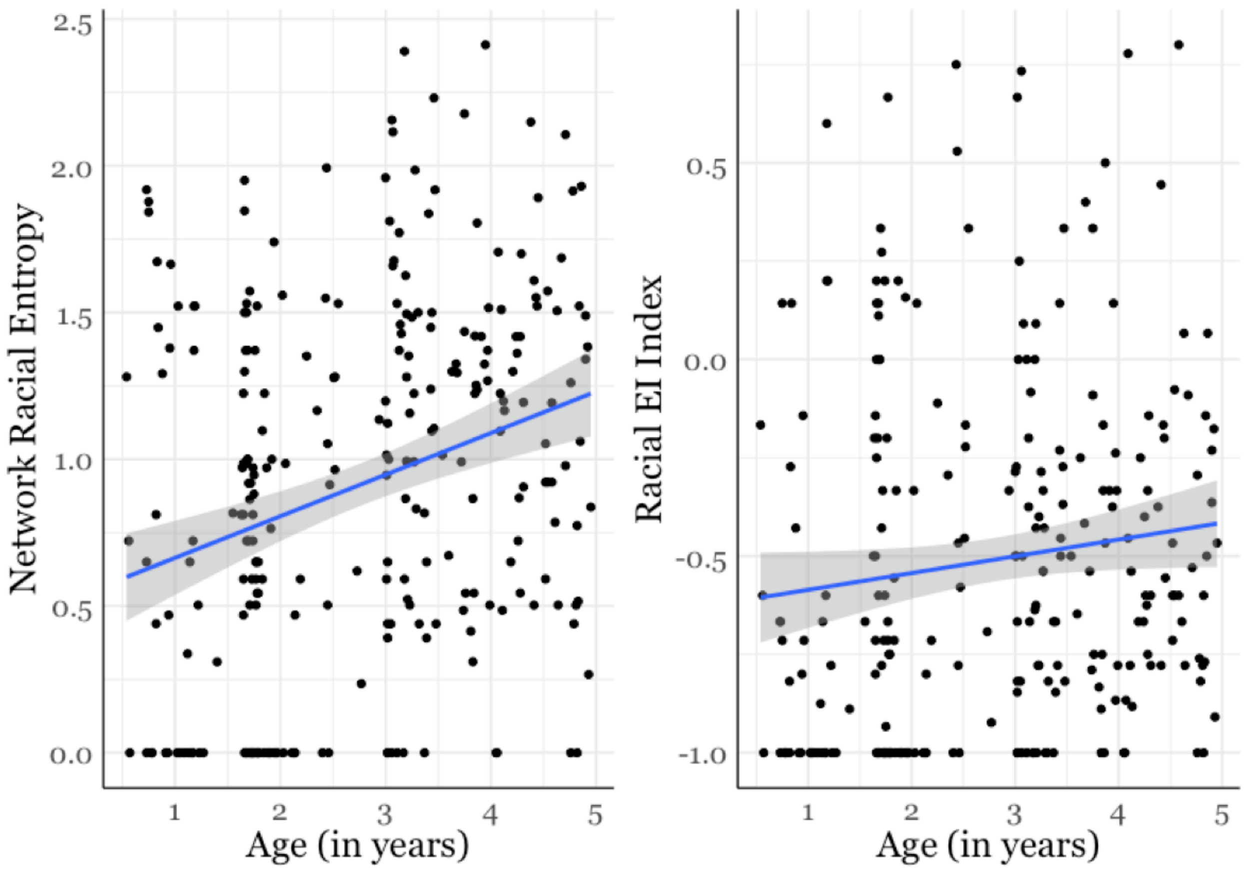
Network Racial Entropy and Racial EI Index



Note. The two measures of network racial diversity were highly correlated with each other (*rho* = 0.72, $p < 0.001$).

Figure 14

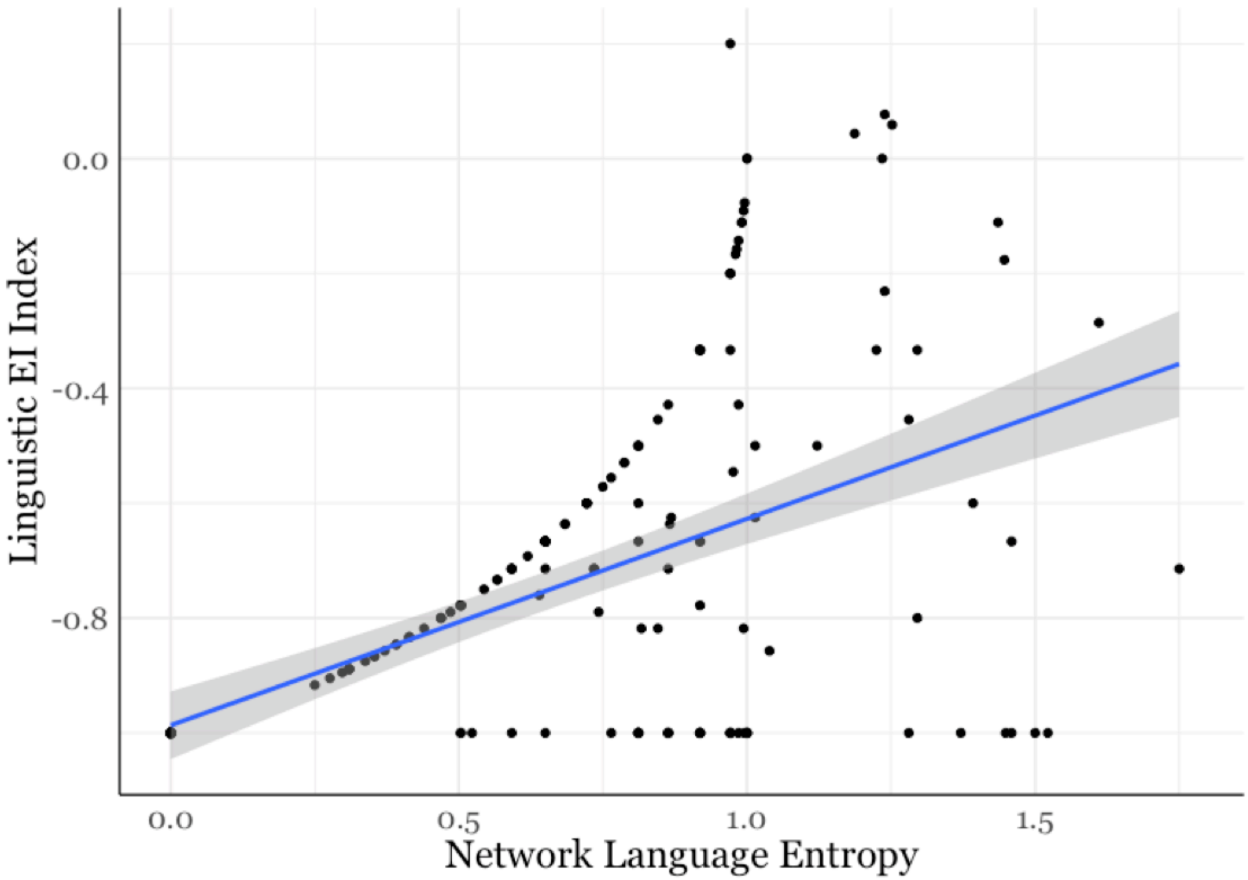
Network Racial Diversity and Age



Note. There was a significant positive correlation with age for Network Racial Entropy (*rho* = 0.25, *p* <0.001) and for Network Racial EI Index and age (*rho* = 0.16, *p* = 0.01).

Figure 15

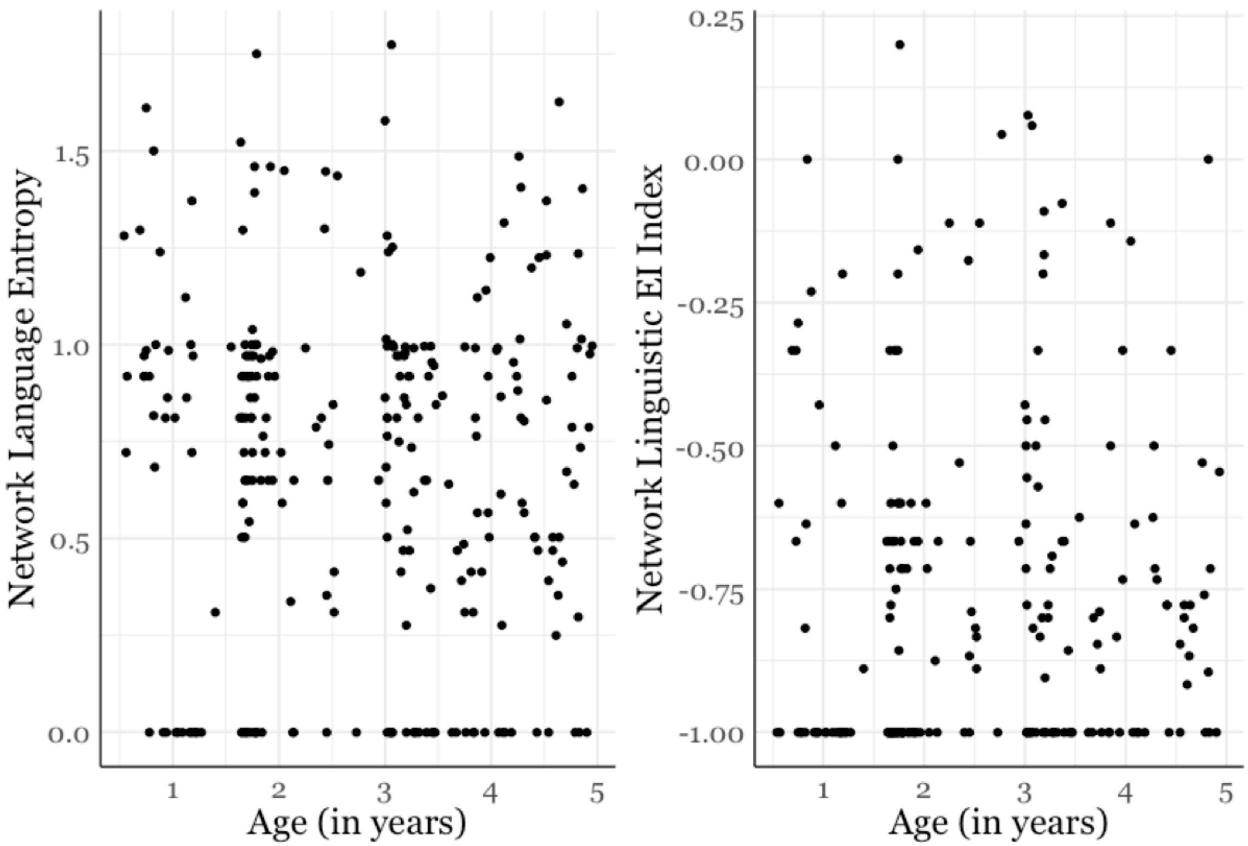
Network Language Entropy and Linguistic EI Index



Note. The two measures of network linguistic diversity were highly correlated with each other (*rho* = 0.50, *p* < 0.001).

Figure 16

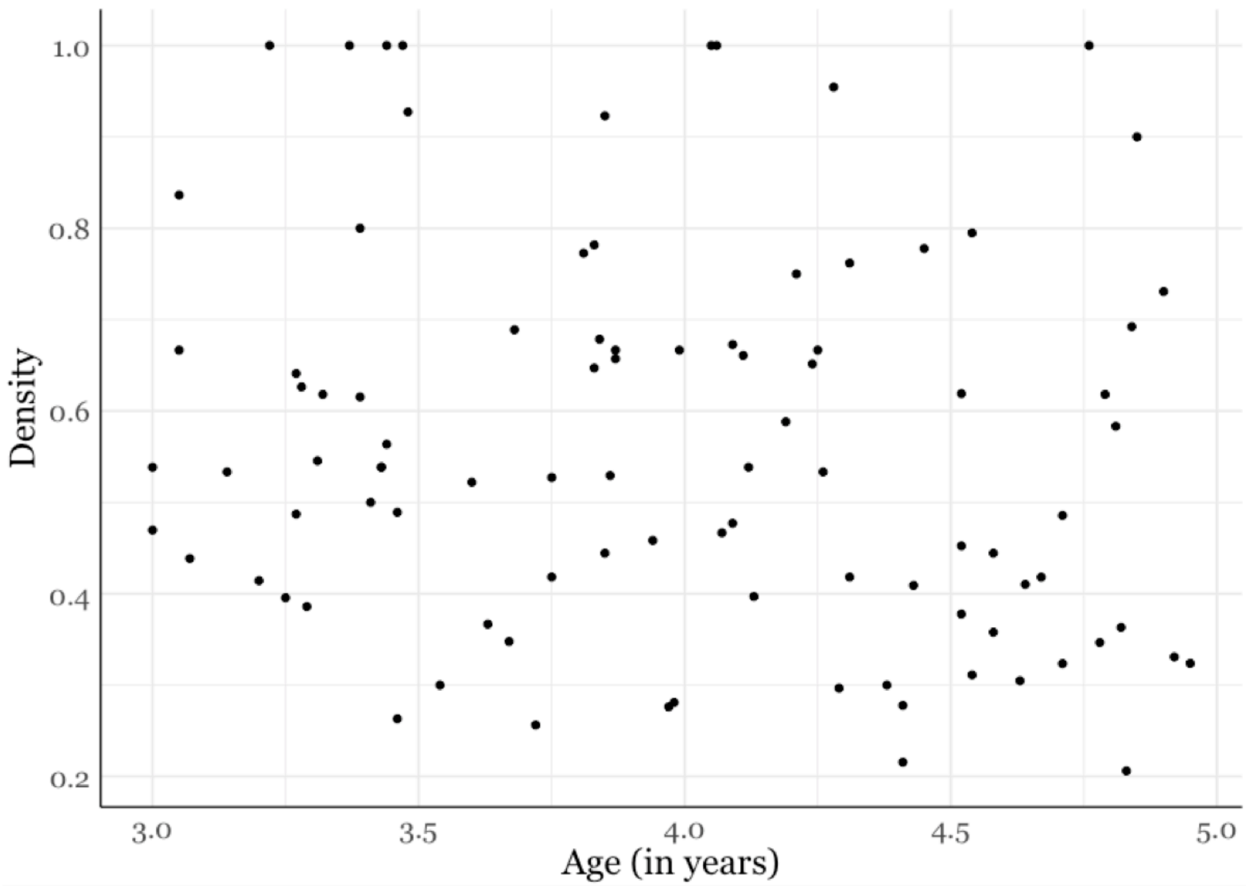
Network Language Entropy and Age



Note. There was no evidence that Network Language Entropy (*rho* = -0.07, *p* = 0.29) or Network Linguistic EI Index (*rho* = 0.09, *p* = 0.28) was correlated with child age.

Figure 17

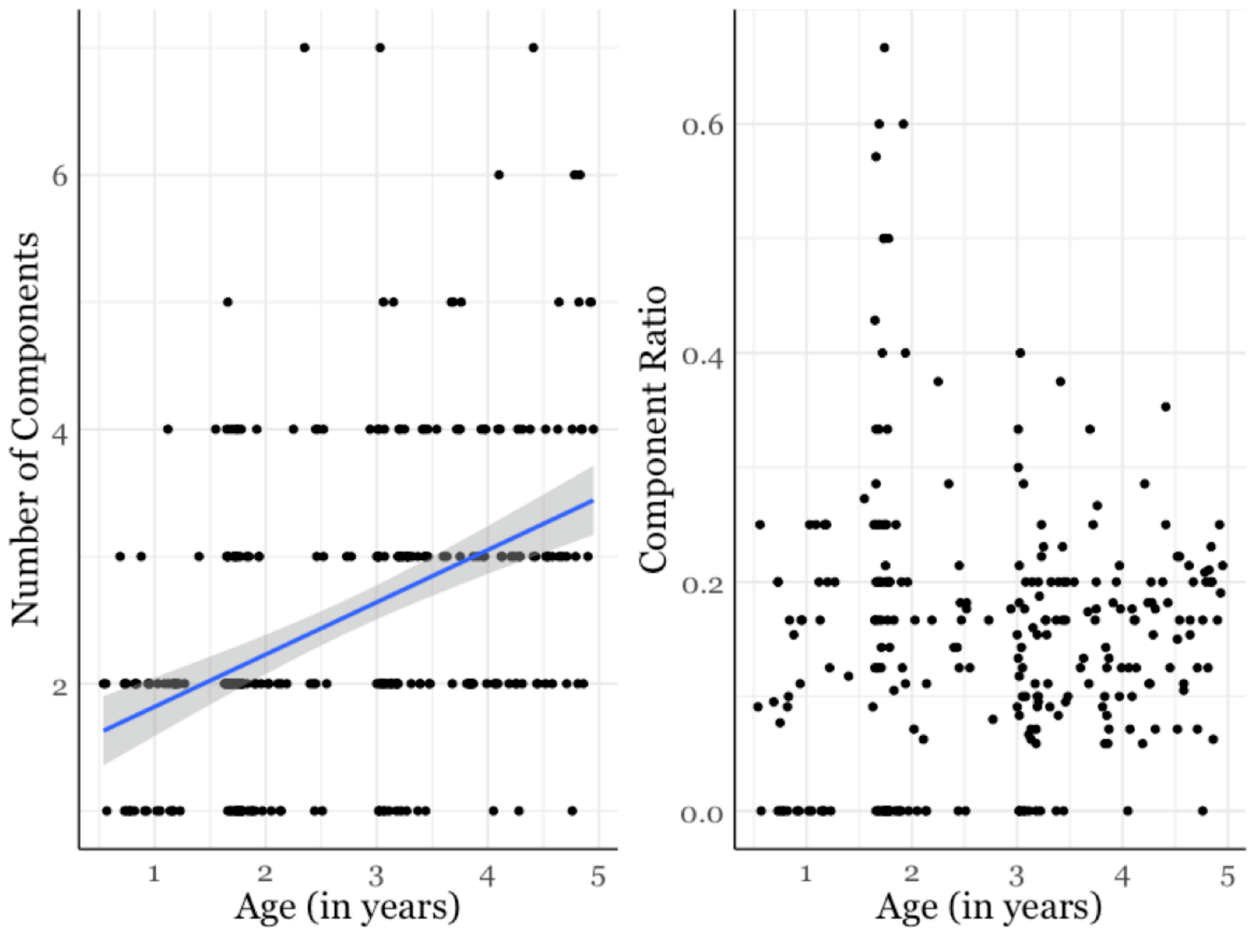
Density and Age



Note. There was no evidence that Density was related to child's age (*rho* = -0.19, *p* = 0.12).

Figure 18

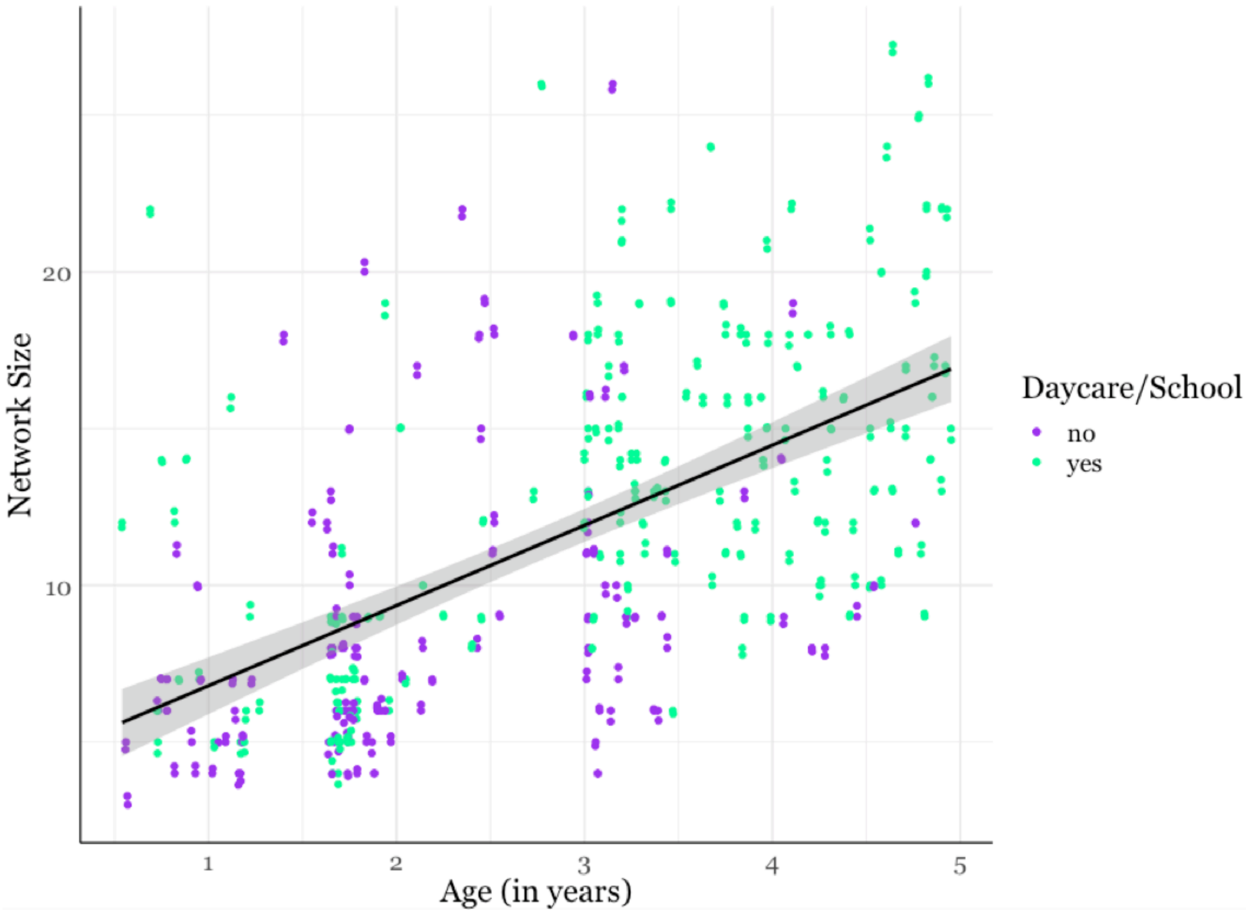
Number of Components, Component Ratio and Age



Note. The number of components was positively correlated with age – as children got older the number of components in their network increased (*rho* = 0.63, $p < 0.001$). The Component Ratio was not correlated with age; there was no evidence that the fragmentation of children's networks varied with age (*rho* = 0.04, $p = 0.59$).

Figure 19

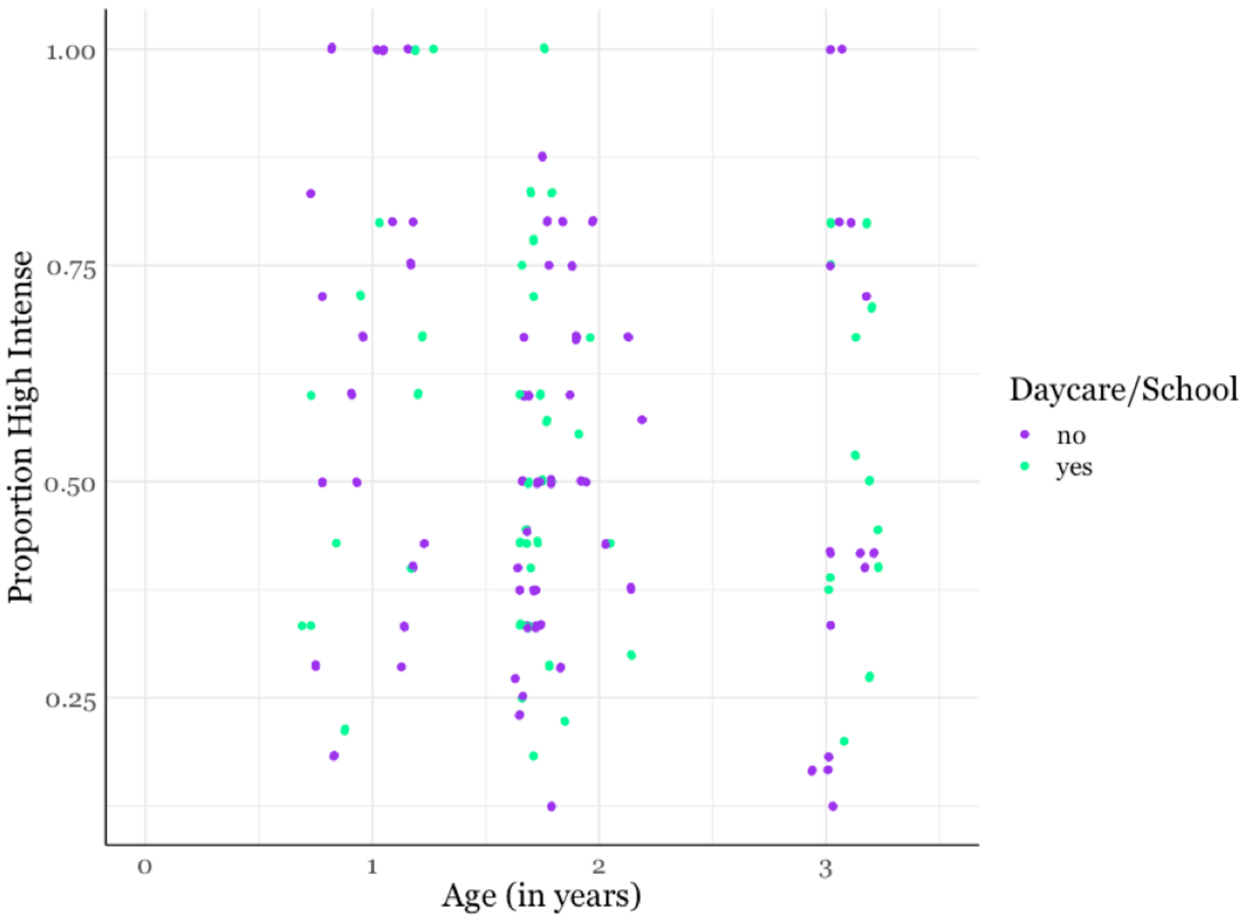
Network Size, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare, and the interaction on Network Size and the regression was significant ($R^2 = 0.39$, $F(3, 275) = 61.3$, $p < 0.001$). There was a main effect of age ($\beta = 0.02$, $p < 0.001$), no main effect of childcare experience ($\beta = 0.10$, $p = 0.62$), and no significant interaction ($\beta = 0.006$, $p = 0.28$).

Figure 20

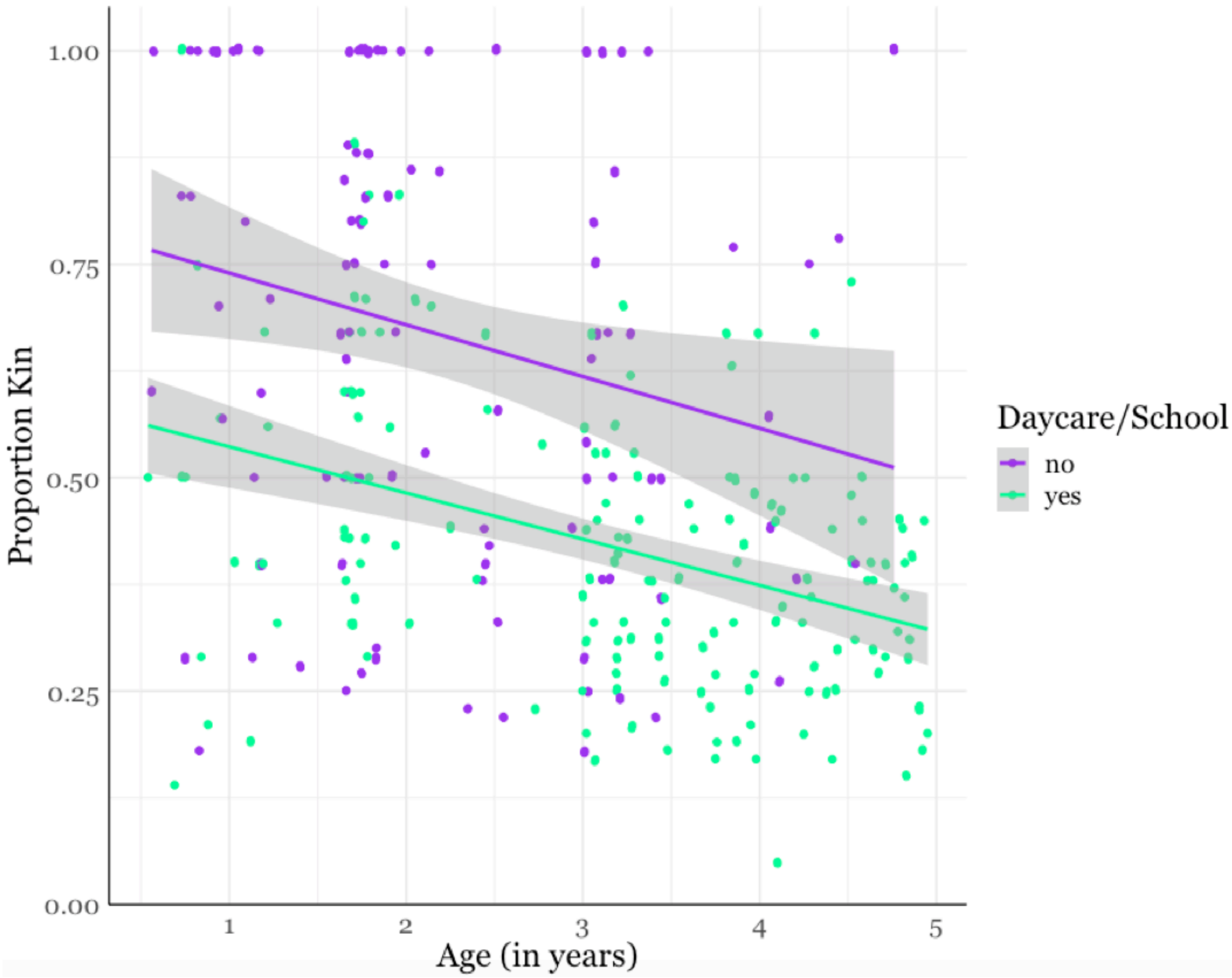
Proportion of High Intense Relationships, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare experience, and the interaction on the Proportion of High Intense Relationships and the analysis revealed a null model ($R^2 = 0.02$, $F(3, 169) = 2.01$, $p = 0.11$).

Figure 21

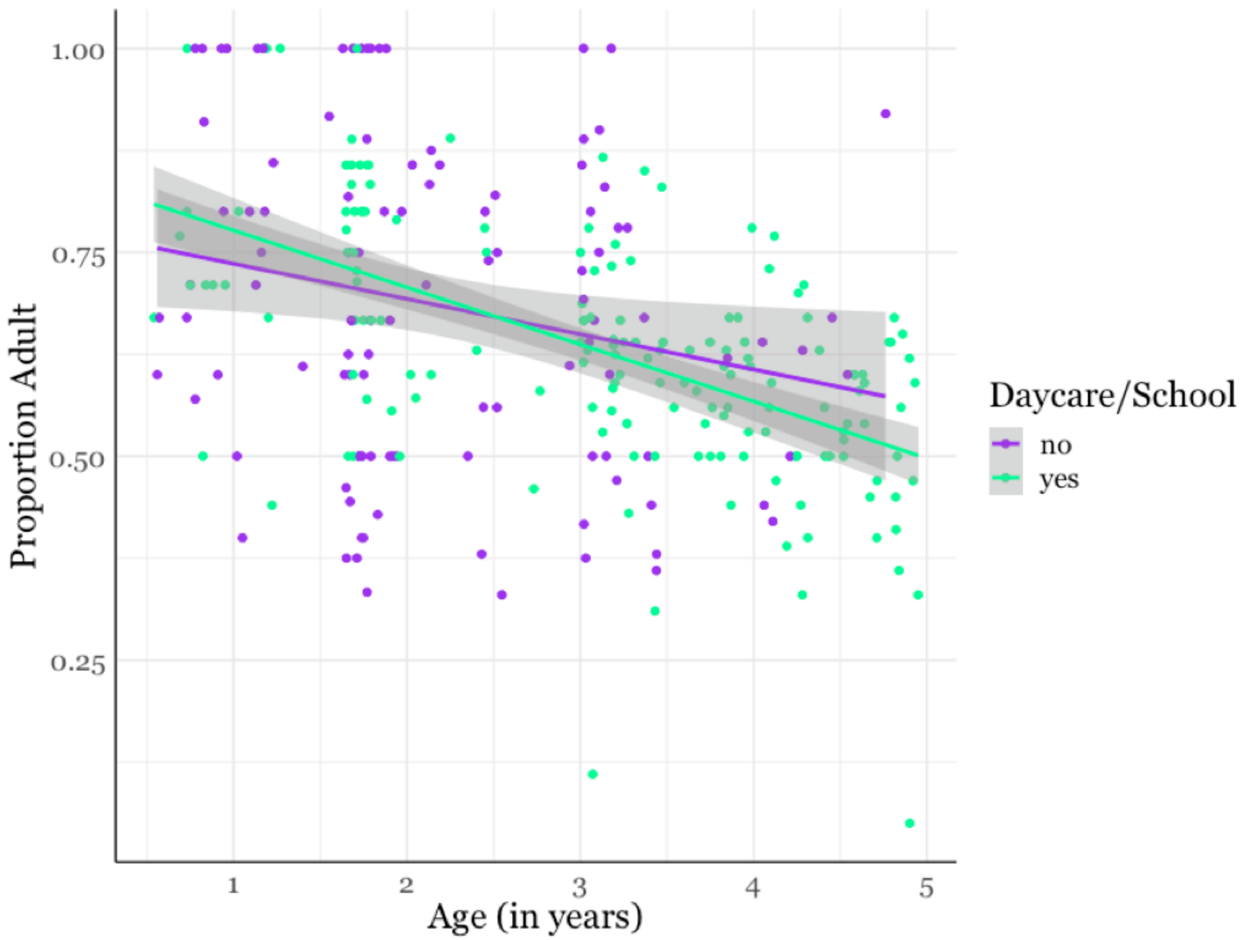
Proportion of Kin, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare experience, and the interaction on the Proportion of Kin Relationships and the regression was significant ($R^2 = 0.30$, $F(3, 274) = 41.5$, $p < 0.001$). There was a significant main effect of Age ($\beta = -0.007$, $p < 0.001$) and School ($\beta = -0.32$, $p < 0.001$), but the interaction ($\beta = 0.002$, $p = 0.44$) was not significant.

Figure 22

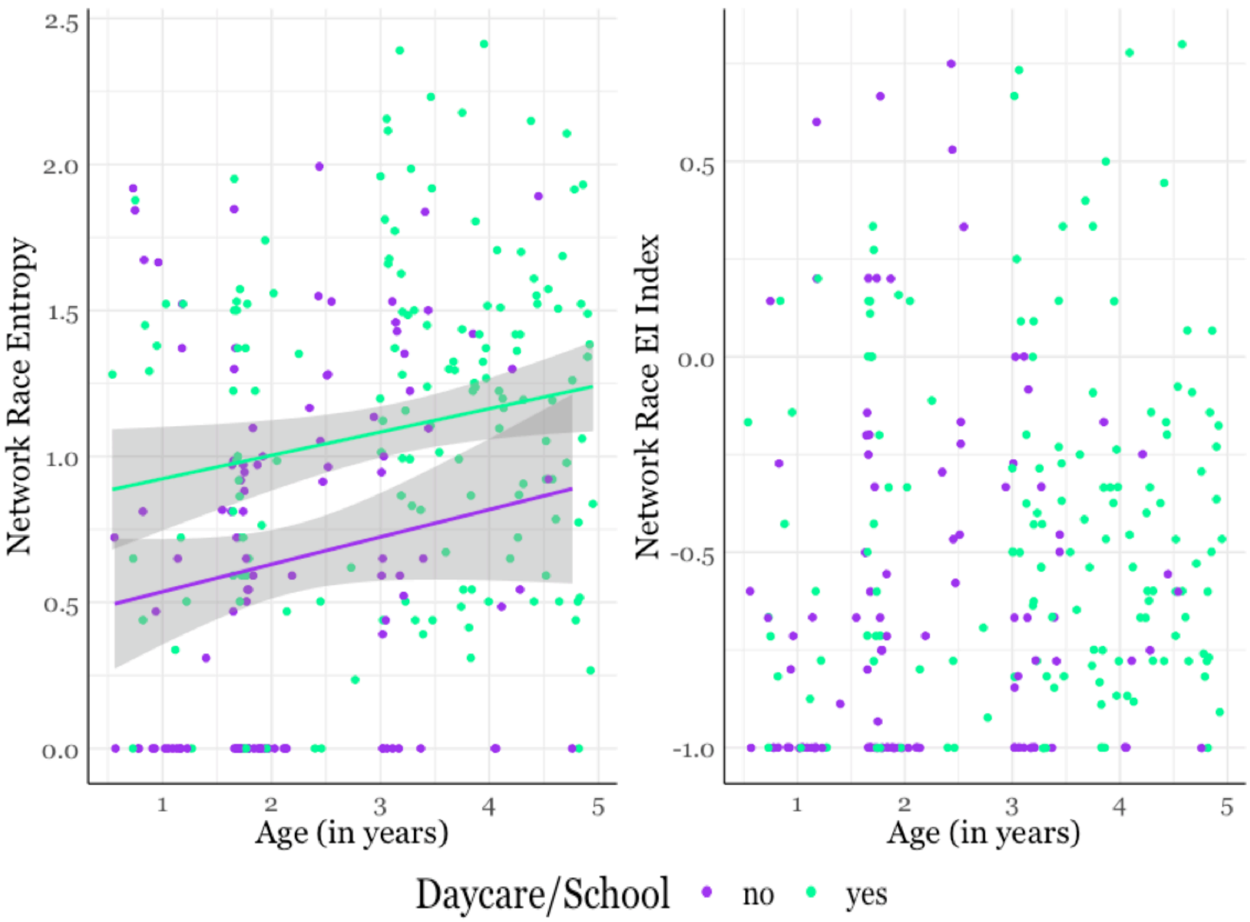
Proportion of Adult, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare, and the interaction on the Proportion of Adult Relationships and the regression was significant (R^2 = 0.18, $F(3, 270) = 21.5$, $p < 0.001$). There was a significant effect of Age ($\beta = -0.004$, $p < 0.005$), but not significant effect of Out-of-home childcare ($\beta = 0.07$, $p = 0.18$), and the interaction ($\beta = -0.002$, $p = 0.15$) was not significant.

Figure 23

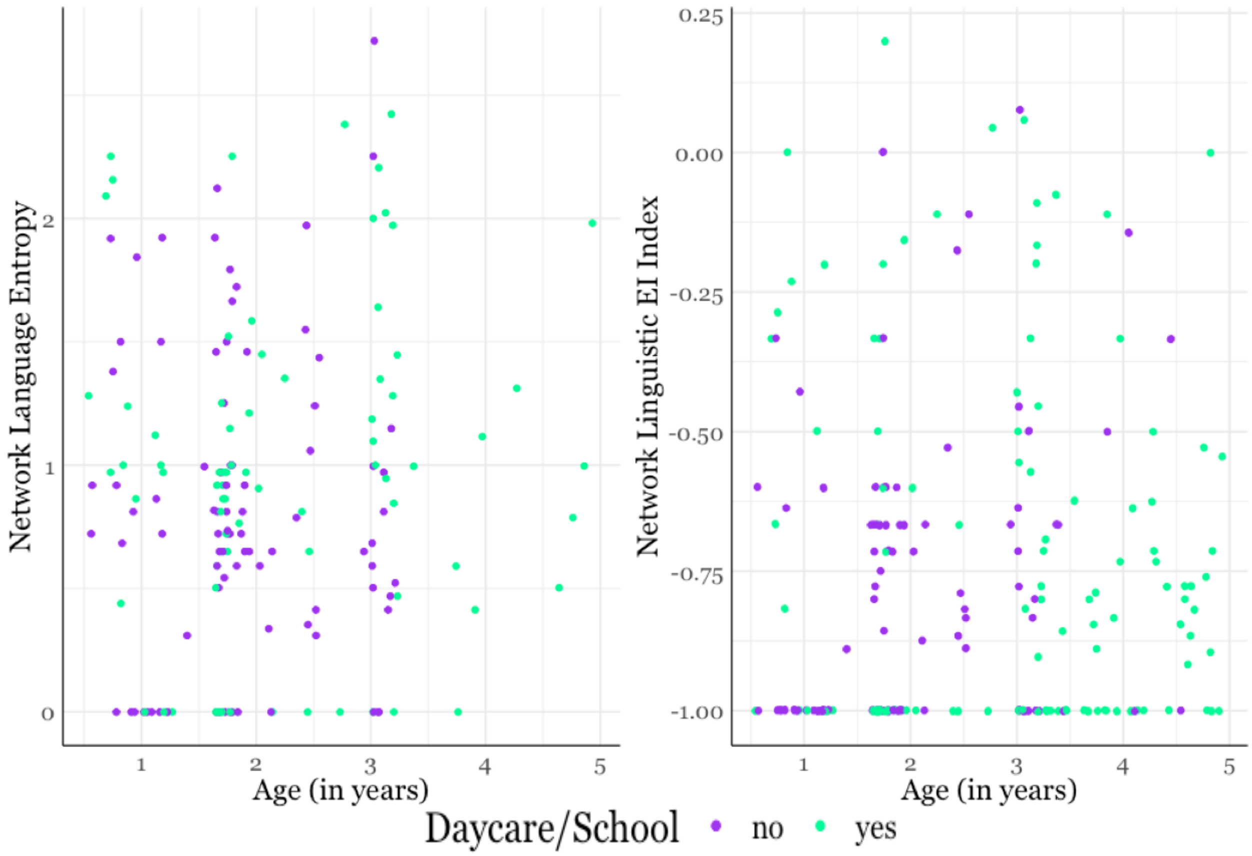
Network Racial Diversity, Age, and Out-of-Home Childcare Experience



Note. The regression with Network Racial Entropy as the dependent variable was significant (R^2 = 0.14, $F(3, 265) = 15.6$, $p < 0.001$). There was no significant effect of Age ($\beta = 0.008$, $p = 0.10$), a significant effect of Out-of-home childcare ($\beta = 0.40$, $p = 0.03$), and the interaction was not significant ($\beta = -0.001$, $p = 0.84$). The regression with Network Racial EI Index as the dependent variable was also significant ($R^2 = -0.001$, $F(3, 249) = 0.85$, $p = 0.47$); there was no effect for Age ($\beta = -0.002$, $p = 0.70$), Out-of-home childcare ($\beta = 0.04$, $p = 0.81$), and the interaction was not significant ($\beta = 0.002$, $p = 0.68$.

Figure 24

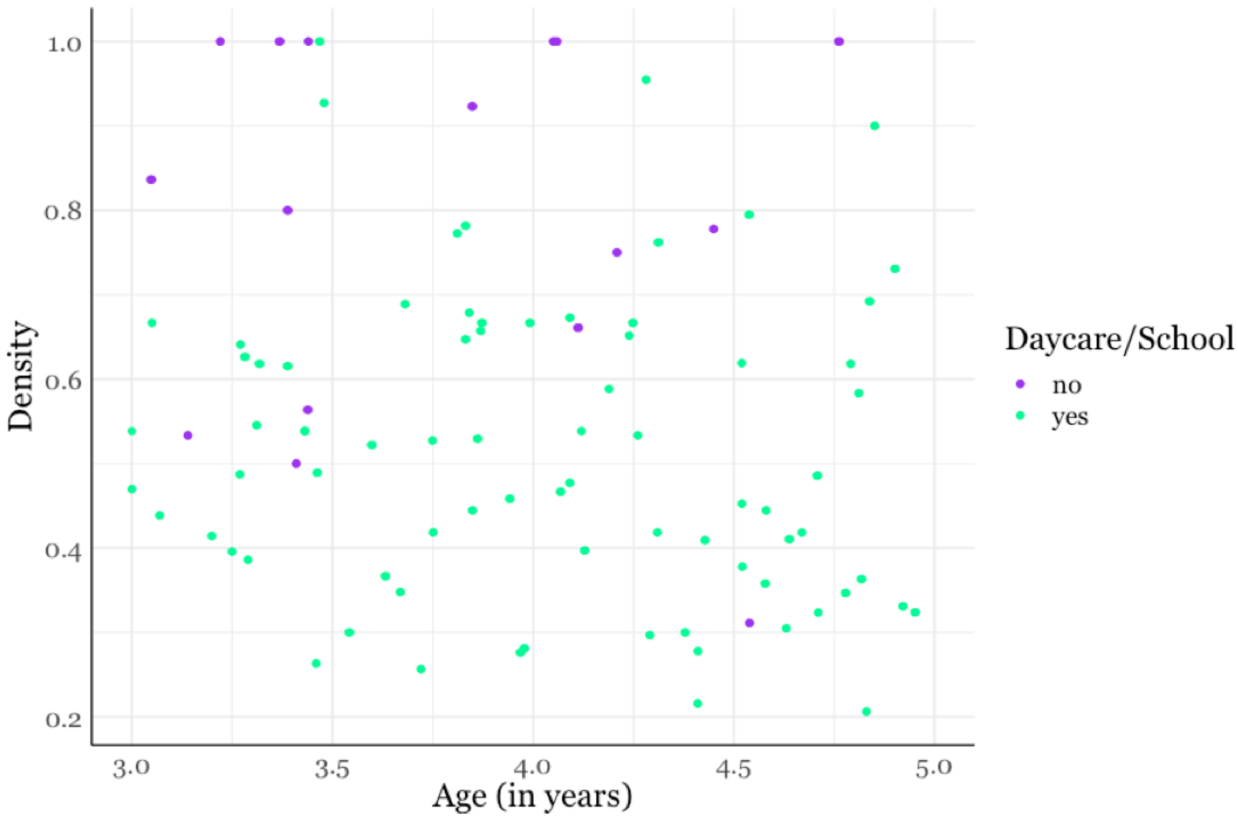
Network Language Diversity, Age, and Out-of-Home Childcare Experience



Note. There was no evidence that either Network Language Entropy (R^2 = -0.003, $F(3, 167)$ = 0.81, p = 0.49) or Network Linguistic EI Index (R^2 = -0.006, $F(3, 210)$ = 1.43, p = 0.23) varied systematically with child age or childcare experience.

Figure 25

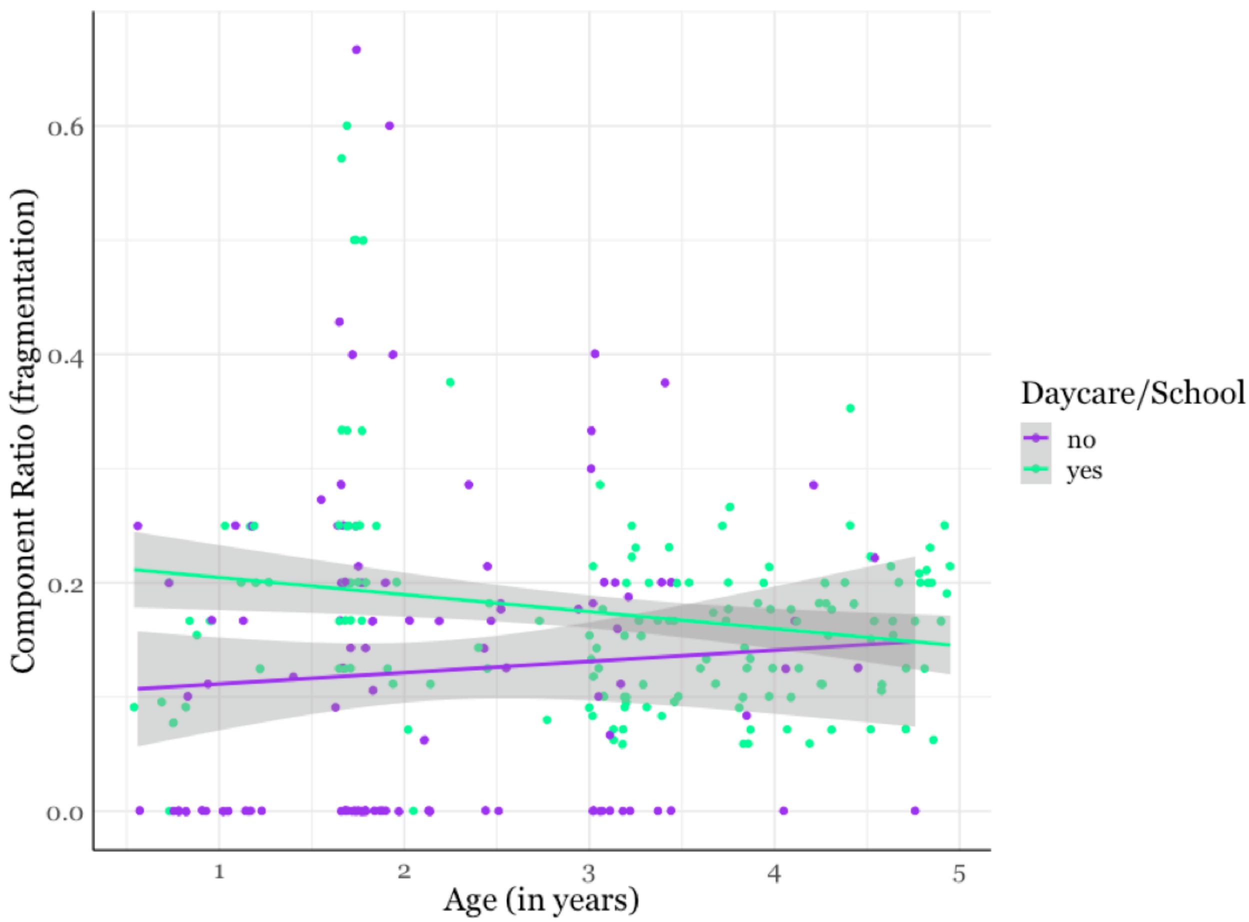
Density, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare, and the interaction on Density and the regression was significant (R^2 = 0.23, F(3, 89) = 9.94, p < 0.001), but revealed null results. There was no effect of Age (β = -0.001, p = 0.87), Out-of-home childcare (β = -0.16, p = 0.67), and the interaction was not significant (β = -0.002, p = 0.77).

Figure 26

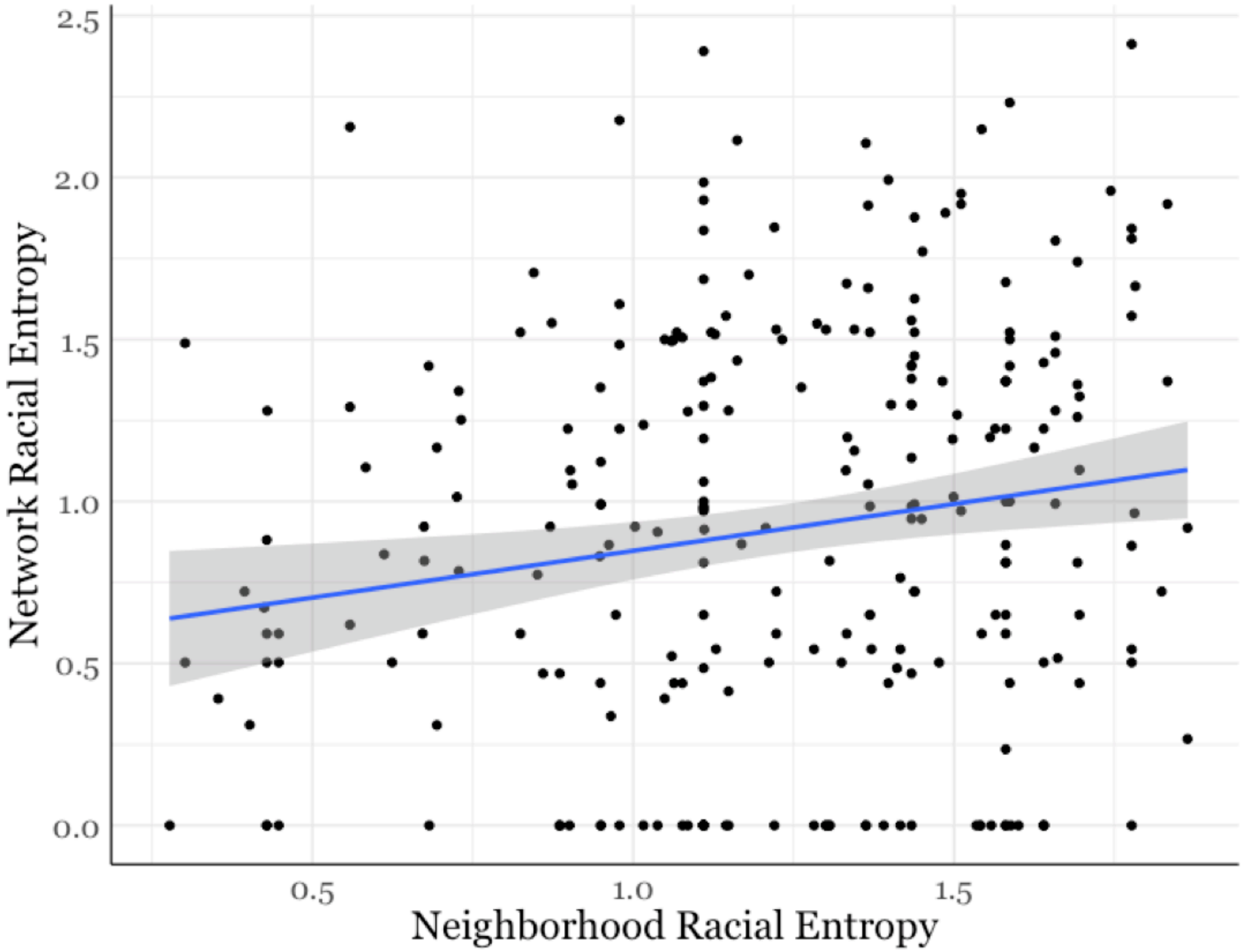
Component Ratio, Age, and Out-of-Home Childcare Experience



Note. A linear regression was conducted to test the effects of Age, Out-of-home childcare experience, and the interaction on the Component Ratio and the regression was significant (R^2 = 0.06, $F(3, 266) = 6.36$, $p < 0.001$). There was no significant effect of Age ($\beta = 0.0002$, $p = 0.86$) and the interaction was not significant ($\beta = -0.001$, $p = 0.21$), but there was a significant effect of Out-of-home childcare ($\beta = 0.10$, $p = 0.004$). Children in school or daycare had more fragmented networks than children not in school or daycare.

Figure 27

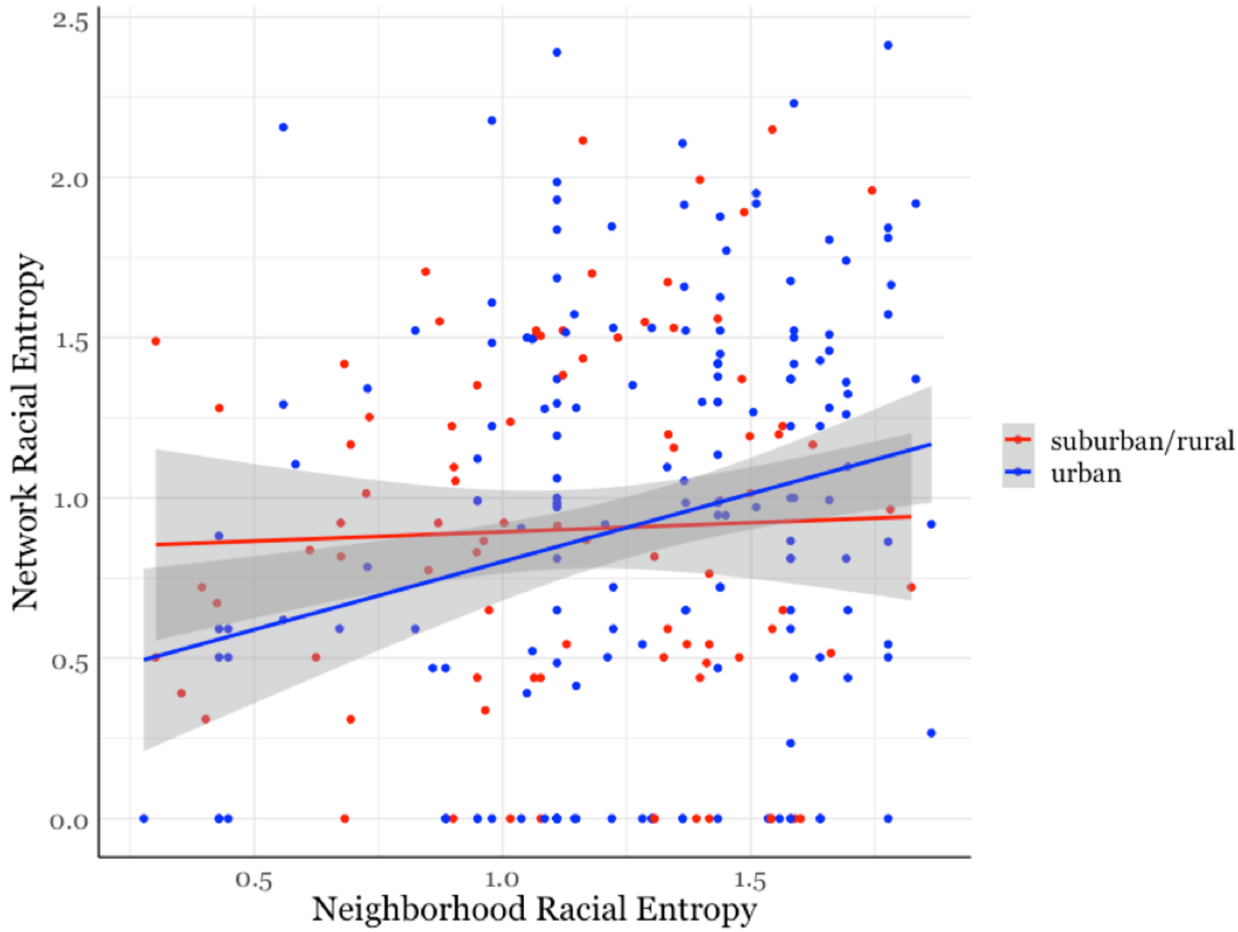
Network and Neighborhood Racial Diversity



Note. There was a positive correlation between Network and Neighborhood Racial Entropy (*rho* = 0.17, *p* < 0.005).

Figure 28

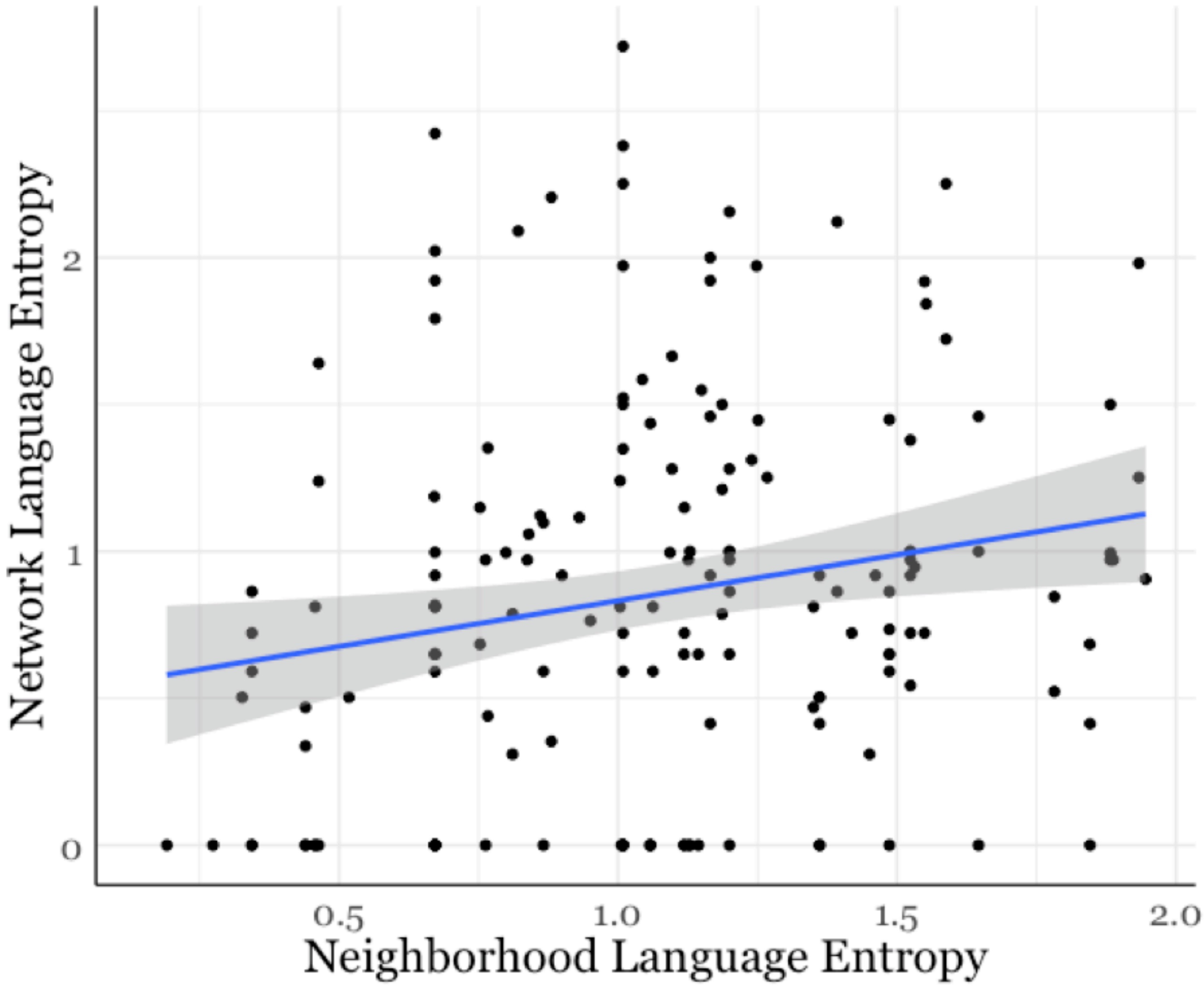
Network and Neighborhood Racial Diversity by Geographic Location



Note. For urban subjects only, there was a positive correlation between Network and Neighborhood Racial Entropy (*rho* = 0.24, *p* < 0.002).

Figure 29

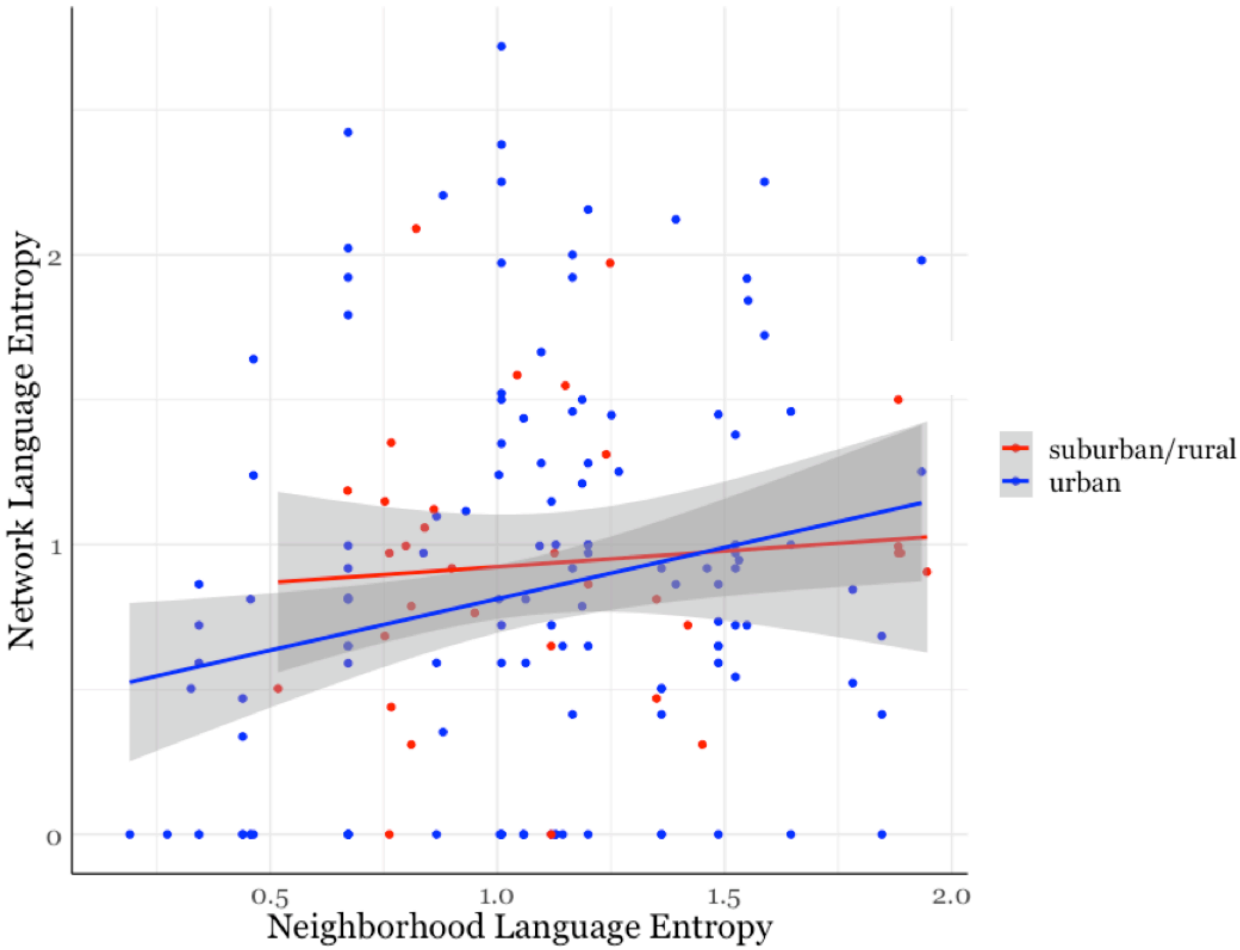
Network and Neighborhood Language Diversity



Notes. Network and Neighborhood Language Entropy were positively correlated with each other (*rho* = 0.22, *p* = 0.004).

Figure 30

Network and Neighborhood Language Diversity by Geographic Location



Note. For urban areas only, there was a positive correlation between Network and Neighborhood Entropy (*rho* = 0.25, *p* = 0.004).

Chapter 2: Children's social network size is related to their perspective-taking skills

Perspective-taking (PT) is a core human competence – it is a skill that is used in conversation (e.g., Keysar et al., 2000), emotional understanding (e.g., Decety & Jackson, 2006), and spatial reasoning (Schober, 1993). To become a successful social partner, children use their PT skills; PT is necessary to react appropriately and in a timely manner in social interactions and it is correlated with later theory of mind skills (Farrant et al., 2006; Harwood & Farrar, 2006; Yeung et al., 2019). PT emerges early in ontogeny (Herold & Akhtar, 2008; Krogh-Jespersen et al., 2015; Liberman et al., 2016) and continues to develop into more robust PT skills around the second and third year of life (Masangkay et al., 1974; Moll & Meltzoff, 2011; Moll & Tomasello, 2006).

Although 2-year-olds start to exhibit visual PT skill in experimental tasks, PT continues to develop and mature throughout the first several years of development (Peskin & Ardino, 2003). One key type of PT is "Level 1 Visual PT," or the understanding that what you see may differ from what someone else sees (Moll & Tomasello, 2006; Masangkay et al., 1974). Understanding what another person can and cannot see is a crucial and early-emerging type of PT necessary for social interactions. Using Level 1 PT in live, social interactions is complex; children have to reason about both what their social partner can and cannot see, do so in a time-sensitive manner, and act accordingly to successfully engage in social interactions. Even adults make mistakes in interactions that require PT. Keysar and colleagues (2000) used a Director task where adult participants moved objects on a grid in response to instructions from a social partner on the other side of the grid. Crucially, participants had full visual access to all objects while their partner's view of some objects was blocked. Although adults are certainly able to understand that differences in perspective can exist, nevertheless participants had difficulties in tracking which objects their partner could and could not see in the task, suggesting that engaging in PT during communicative interactions is a demanding process.

In the first few years of life PT undergoes significant changes. At a time when children are getting better at PT, they also experience rapid changes to their early social environments. In a study using social networks to capture and track children's early social environments, results showed that the social networks of children undergo marked growth from infancy through age 5 (Chapter 1). Older children had larger networks than younger children, and their networks were more likely to include other children and people outside the immediate family (Chapter 1). The question arises whether variations in early social experience might be related to children's emerging PT ability. Prior work suggests two specific predictions: children who interact with more people on a regular basis might be better at PT and children who interact with a more diverse set of people might be better at PT.

Children who interact with more people on a regular basis might have more opportunities to practice their PT skills. This would suggest that social network size might be correlated with PT. Indeed, prior work with adults demonstrated a relation between social network size and PT. Still and Dunbar (2007) tested adults' PT skills in a narrative task where participants answered questions about the intentionality of the characters. Participants also completed a questionnaire that assessed their social network. PT, as indexed by intentionality scores on the task, was correlated with social network size. Thus, adults who were better at PT also had larger social networks. This study is consistent with the broader literature indicating that social network size is correlated with the neural substrates of social cognition for both adults and non-human primates (Bickart et al., 2011; Sallet et al., 2011). However, the social networks of children and adults are drastically different from one another. Adults' social network size is relatively stable throughout adulthood (Perry & Pescosolido, 2012; Suitor & Keeton, 1997), but children's networks may change and be variable in ways that are different from adult networks (Chapter 1). The substantial variation in network size during the first few years of life raises the question of whether variation in the number of people in the social network is correlated with children's social cognitive skills, particularly considering another's perspective. The present study examined whether the size of children's social networks was correlated with their PT abilities.

As children's networks grow and expand, children have the opportunity to interact with a more diverse set of people. For instance, children may interact with people who are not immediate family members, people who are of different races, and people who speak different languages. The study from Chapter 1 found that as children's network size increased, so did the racial and linguistic diversity in the social network. It is possible that children who interact with a more diverse set of people, specifically diverse language speakers, might be better at PT because children could gain experience with tracking who knows what content and which speakers can communicate with one another. Indeed, prior research suggests that diverse language environments are related to PT. For example, Fan and colleagues (2015) found that 4- to 6-year-old children who were either bilingual or had exposure to other languages more accurately considered another person's perspective than monolingual children. Similarly, 16-month-olds who regularly heard multiple languages performed better than infants who only heard English (Liberman et al., 2016). These findings are consistent with prior work that has found a bilingual advantage for children's social cognitive skills; 8-year-old bilinguals were found to be better at PT than monolinguals (Greenberg et al., 2013) and preschool-aged bilinguals were better at both PT and false belief understanding than monolinguals (Goetz, 2003).

This raises the possibility that children in more linguistically diverse networks may have superior PT skill. It should be noted that prior studies about language exposure and PT measured children's contact with languages other than English, but did not measure who the speakers were or how many languages were spoken. Thus, it remains an open question whether contact with other *languages* matters or whether contact with other-language *speakers* relates to PT. By collecting detailed information about children's social networks, the present study tested whether contact with people speaking different languages related to PT, beyond mere exposure to other languages.

Taken together, prior work suggested that adults with larger social networks had better PT skills and that variations in children's early social environments might be related to their PT ability. To better understand the structure and properties of children's early social environments, I leveraged the tools of social network analysis. Social network analysis provides a novel approach to understand how variations in social experience relate to social cognition (Chapter 1). Here, the network measures Network Size (the number of people in children's social networks) and Network Linguistic Diversity (the diversity of language speakers in children's social networks) were used to examine whether size or language diversity related to children's PT skills. Social network analysis considers several dimensions of social experience at once, which makes it an excellent tool to test how different aspects of social experience relate to PT.

In particular, the present study addressed two questions. First, does social network size correlate with young children's PT skill? Second, does the diversity of language speakers in a child's network correlate with their PT skill? To test these questions, 3-year-olds participated in a behavioral PT task (Brezack et al., *in press*) and parents completed *The Child Social Network Questionnaire* (Chapter 1), which measured the structure and properties of children's social networks. Given the prior literature, I predicted that children in larger social networks and children with more diverse language speakers in their networks would have superior PT skill. The hypotheses and analysis plan were preregistered (https://aspredicted.org/blind.php?x=xx2wz8).

Methods

Participants

Participants were recruited from Chicago, IL (USA) using a database of families who volunteered to participate in early childhood research. This study was approved by the Institutional Review Board at the University of Chicago (H10193: H10193-P01). Thirty-six 3-year-olds (M_{age} = 37.3 months; range = 36.0 - 38.9 months) participated in the behavioral PT task (Brezack et al., in press) as part of a larger study on PT development in a lab at a large research university. The present study was a follow-up study to the behavioral PT task. After the children participated in the PT study, parents were contacted over the phone to participate in *The Child Social Network Questionnaire* (Chapter 1). Thirty-one subjects (M_{age} = 37.2 months, range 35.3–38.8 months; *n* = 15 female, *n* = 16 male) completed the phone interview. The average time between in lab and interview was 2.2 months (range: 10 days – 164 days). Network Size was determined from the phone interview for those children. Of those 31 children, parents of 27 subjects completed the online demographic forms of *The Child Social Network Questionnaire*, which measured children's Network Linguistic Diversity. Thus, there was Network Size data for 31 children and Network Linguistic Diversity data for 27 children. The final sample of 31 children was 67.8% European-American, 6.5% African-American, 3.2% Hispanic, 3.2% Asian, and 12.9% multiracial. 70% of the subjects (*n* = 21) were monolingual English speakers. Subjects that were recruited for this study had to hear at least 75% of English at home because the PT task required proficiency in the English language. Maternal education was collected to assess socio-economic status and 73% of the sample ($n = 22$) had mothers with a bachelor's degree or higher.

Perspective-Taking Task

In the PT task, the child participated in a social communicative interaction with an experimenter (E1). Children sat across from E1 at a table. The child's task was to hand E1 a requested toy, which the child could identify through considering the experimenter's visual perspective on the toys. More specifically, on each trial, children chose one of two identical toys to give to E1 based on audio prompts requiring taking E1's perspective. E1 could only see one of the two toys while the child could always see both toys. To begin each trial, E1 opened one of two doors of a puppet stage (either right or left side) so she could see one of the two toys (see Brezack et al., in press for more details). Then, children were instructed with an audio prompt which toy to hand E1. Children were prompted to either hand E1 the toy that she could see (Can See trials: "It's the one [*E1 name*] can see!") or the toy that she could not see (Does Not See trials: "It's the one [*E1 name*] does not see!"). On the Can See trials, E1 and the child shared visual access on the requested toy. On the Does Not See trials, E1 could not see the requested toy. These two trial types were included in the design to cover different visual access scenarios.

Children were separated from the toys by a clear plastic barrier. After the instruction which toy to choose, a second experimenter waited 2 seconds (during which children's eye gaze was measured) before lowering the barrier so the child could choose a toy and pass it to E1. Eye gaze during the 2-second window was coded off-line for a measure of implicit PT performance. Children's toy choice after the barrier was lowered was coded as a measure of explicit PT performance. There were two blocks of PT trials, with Can See and Does Not See trials interleaved, the correct answer side counterbalanced, and 8 trials per block. There were also two blocks of control trials. The control trials were either Red trials ("It's on the *red* side!") or Yellow trials ("It's on the *yellow* side!"). The requested toy corresponded to the color mat on which the toy sat. The control trials did not require PT and were thus not further analyzed here. A warm-up phase preceded the task and a Catch Trial after each block ensured children were paying attention to the task. See Supplementary Materials and Brezack et al. (in press) for additional task details.

After completing the PT task, children completed other measures to assess their cognitive ability as part of the previous study (Brezack et al., in press). Importantly, children were tested on the Toolbox Picture Vocabulary Test (TPVT) to assess their vocabulary. The standardized TPVT scores were used in the analyses to control for vocabulary and age.

Calculating Perspective-Taking Performance

Children's PT performance was assessed with two measures of PT understanding: an explicit measure of PT and an implicit measure of PT. Explicit PT performance was measured by calculating the proportion of trials on which the child correctly handed E1 the toy E1 could see or could not see, thereby accurately accounting for E1's perspective. Implicit PT performance was measured by eye gaze: The proportion of time children spent looking at the correct compared to the distractor object was measured during the time window immediately following the audio prompt ("It's the one *[E1 name]* [can see/does not see]!") until the frame before the clear barrier was lowered. Explicit and Implicit PT proportions were arc-sine square-root transformed for analysis. Coding was performed in Mangold Interact (2017) at a rate of 30 frames per second by a coder blind to the research hypotheses. A separate coder coded 22.2% of the sessions; reliability was high (explicit PT: Cronbach's alpha = 0.999; ICC = 0.999, $F(7) = 836.5$, $p < .001$; Implicit PT: Cronbach's alpha = 0.978; ICC = 0.969, $F(7) = 46.4$, $p < .001$).

The Child Social Network Questionnaire

The Child Social Network Questionnaire is a method designed to assess infants' and children's social networks (Chapter 1). Young children's social networks are composed of the people that the child interacts with on a regular basis – a child's social network captures both the number of people they interact with on a regular basis (Network Size) and attributes of the people, which make-up the diversity of the social network (race, languages they speak, gender). *The Child Social Network Questionnaire* is administered in two parts: 1) a parent interview to collect information about children's typical week of activities, and 2) a survey to collect demographic information for each person the child sees regularly.

For the parent interview, the participants' parents were contacted over the phone after they completed the PT task in the lab. The goal of the parent interview was to generate a list of people the child interacts with on a regular basis. Parents were asked to describe their child's "typical week" of activities. Parents' description of their child's typical schedule served as a memory prompt and allowed the experimenter to assess children's close, personal relationships. The interview was explained as follows: "First, we will do an interview where I will ask you to describe [CHILD's] typical week. We want to understand the different people [CHILD] sees in a typical week and what kinds of activities [she/he/they] does with those people. I am going to ask you about times [CHILD] wakes up, goes to sleep, and takes a nap so we can get a rough measure of amount of time they spend with different people. After the interview, I will create a form for each of the people you mentioned and send you a Qualtrics link for you to fill out. Starting with Monday, what time does your child wake up and what happens after that?" After parents described their child's schedule for Monday through Sunday, the experimenter asked, "Is there anyone else that you think is worth mentioning that your child sees on a regular basis?" The following measures were derived from the interview: 1) a list of people the child interacts with on a regular basis, which is the child's social Network Size, and 2) the proportion of time each of those people spend with the child. After the phone interview, parents received a customized Qualtrics link with a demographic survey for each of the people in their child's social network. For an example of the demographic survey, see Appendix B.

Metrics Calculated for Children's Social Networks

The Child Social Network Questionnaire provides rich data about children's early social networks. While there are several metrics that can be calculated from *The Child Social Network Questionnaire*, the present study focused on Network Size and Network Linguistic Diversity (as assed by Language Entropy), as these were critical to address the research questions.

Network Size. Network Size was the total number of people (also called 'nodes') the child sees on a regular basis. This number was determined from the phone interview. A parent had to report that the child knew each person individually for that person to be counted as a node. For example, if a parent reported that the child was in daycare or preschool, the experimenter would ask, "Are there any kids in the class that stand out as friends?" Parents reported between 0-10 different friends, and each friend was an individual node. Most nodes in children's social networks were individual people; however, there were some "group level" nodes. For example, there were nodes for "daycare/preschool class;" this node represents a group of children in which no children were individuated as the child's friend. The count variable of Network Size was square-root + .5 transformed for analyses (Kirk, 2013).

Importantly, children's Network Size could be related to their participation in school or daycare. There is a robust literature demonstrating that experience with school is related to superior cognitive development (see Ceci, 1991 for a review). Given potential indications in the literatures on influence of school attendance on social cognition, it was noted whether children attended school or daycare to test whether any effect of Network Size was due simply to school attendance. Children were classified as either attending or not attending school based on the responses from *The Child Social Network Questionnaire*.

Network Language Diversity. There are two conceptually distinct measures to define network diversity –entropy and EI Index. Entropy describes the representation of different social groups in the network, while the EI Index indicates how diverse the network was relative to the child. The measure most similar to prior developmental work is entropy – this measure describes the different language speakers present in children's networks. The analysis primarily focused on how Language Entropy was correlated with PT. See Supplemental Materials for the analysis on Linguistic EI Index and PT. See Chapter 1 for more details about how to measure and define network diversity.

Language Entropy. In network science, entropy indicates the relative presence of different social categories among the nodes in a network and is calculated as follows for a given probability vector of P(X): $H(X) = - \sum P(X) * log2(P(X))$ (Drost, 2018; Krenz et al., 2020; Shannon, 1948). To calculate Language Entropy, each node in the social network needed to fit into a discrete category of language speaker. The language categories were determined based on the sample. Parents provided detailed information about the languages each of the nodes spoke. Data was not collected on whether and how often these languages were directed at or spoken around the child; I instead analyzed whether each node spoke the language. All children in this sample had monolingual English speakers represented in their network. An entropy score of 0 means there is no diversity of category; for this particular sample, a score of 0 indicates all the alters were monolingual English speakers An entropy score of 1 indicates that there is equal amounts of two different categories. For example, a child could have a Language Entropy score of 1 if their network was half monolingual English speakers and half English/Spanish bilingual speakers. See Supplementary Materials for a full list of all the discrete language categories in this sample.

Results

Perspective-Taking Task Performance

Before asking about individual differences, children's performance on the task was assessed at a group level. A 2x2 (Trial Type: Can See/Does Not See x Measurement Type: Explicit/Implicit) repeated-measures ANOVA revealed a main effect of Trial Type, such that children performed better on the Can See trials than the Does Not See trials ($F(1,86) = 8.40$, $p < .01$) There was no significant main effect of Measurement Type ($F(1,86) = 1.93$, $p > .05$), suggesting no difference between Explicit and Implicit PT, and there was no significant interaction ($F(1,86) = 1.87$, $p > .05$; Figure 31). Follow-up t-tests with a FDR correction confirm that for Explicit PT, children performed above chance (0.50) for the Can See Trials ($M = 0.59$, $SD = 0.21$; $t(29) = 2.31$, $p < .05$). There is no evidence that they performed above chance for the Does Not See Trials ($M = 0.49$, $SD = 0.19$; $t(29) = -0.09$, $p > .05$). For Implicit PT, children performed above chance for Can See Trials ($M = 0.62$, $SD = 0.13$; $t(29) = 4.44$, $p < .001$) and for Does Not See Trials ($M = 0.57$, $SD = 0.15$; $t(29) = 2.99$, $p = .01$). Thus, though children demonstrated awareness of another's perspective in both Can See and Does Not See trials when measured implicitly, they did not consistently implement this understanding in their explicit performance for the Does Not See trials. PT performance results parallel those of the full sample of 36 children reported in Brezack et al. (in press).

The next analysis explored whether Network Size or Network Linguistic Diversity related to PT performance on both types of PT trials. Although it was preregistered to analyze average PT performance across the trial types, there was a significant difference between trial types, which suggested to instead analyze performance on Can See and Does Not See trials (rather than averaging); otherwise, analyses follow those that were preregistered. Linear Mixed Effects Models were run with Trial Type as a factor and Subjects as a random effect because each subject contributed two scores (one for each trial type). Models were run with the lmertest package in R (Kuznetsova et al., 2017). As preregistered, TPVT was tested to see if it related to Explicit or Implicit PT performance, but no relations were found (all p's > .05), so TPVT was not included in subsequent analyses. Per the pre-registration, Explicit PT performance and Implicit PT performance was analyzed in separate analyses and Network Size and Network Linguistic Diversity in separate analyses.

Network Size and Perspective-Taking

On average, children's Network Size was 12 people (SD = 4.01 people, range = 4-18, one outlier removed: 26; see Figure 32). The model predicting Explicit PT from Trial Type and Network Size showed a main effect of Trial Type (β = .89, p < .01) such that performance was higher on Can See Trials than Does Not See Trials. The model also revealed a main effect of Network Size (β = .15, p = .05), indicating that children with more people in their social network demonstrated better Explicit PT performance. There was also a significant interaction between Network Size and Trial Type (β = -.22, p < .05). Post-hoc FDR corrected correlations did not reveal evidence of a relation between performance on the Can See trials and Network Size (r = -

0.13, $p > .05$). However, there was a marginal correlation between performance on Does Not See Trials and Network Size ($r = .40$, $p = .057$), suggesting that children with smaller networks performed worse on the Does Not See Trials than children with larger networks (Figure 33). Children in smaller social networks demonstrated poorer performance on PT trials where their view differed from that of their partner. In this more challenging PT situation, children only performed well when they were in larger social networks.

The same model was performed to test the effect of Network Size on Implicit PT performance. The model revealed null results: There was no significant main effect of Trial Type ($\beta = -.06$, $p > .05$) or Network Size ($\beta = .04$, $p > .05$) and the interaction was not significant ($\beta = .02$, $p > .05$; Figure 34). There was no evidence that Network Size was related to children's implicit PT performance.

Exploratory Analysis Examining the Influence of Daycare/Preschool Attendance

One possible explanation for the finding that having a larger Network Size was correlated with better Explicit PT performance is that Network Size indexes the effects of school on cognition. In the sample, children who were in Daycare or Preschool had larger social networks than children who were not in school (Daycare or Preschool: $n = 15$; $M_{NetworkSize}$ =14 people; No Daycare or Preschool: $n = 15$; $M_{NetworkSize}$ = 10 people; $t(23) = -2.94$, $p < 0.01$; Figure 35). It is possible the Network Size finding is masking an effect of school on PT understanding. Half of the sample ($n = 15$) was in Daycare or Preschool, so an exploratory analysis was performed to test whether being in Daycare or Preschool was related to Explicit PT performance.

The same Linear Mixed Effect model as above was performed with Explicit PT performance as the dependent variable, including Daycare as a fixed effect. The results showed a main effect of Trial Type ($\beta = .19$, $p < .05$), consistent with the previous model, but there was no significant main effect of Daycare ($\beta = .15$, $p > .05$) and no significant interaction ($\beta = -.12$, $p > .05$; Figure 36). The same analysis was performed with Implicit PT performance as the dependent variable – there were no significant main effects and no significant interaction (all p's $> .05$). There was no evidence that being in Daycare or Preschool was related to PT performance, but there is evidence to suggest that Network Size is related to PT performance.

Language Entropy and Perspective-Taking

Children's Language Entropy was on average 1.03 ($SD = 0.79$, range = 0 – 2.72; Figure 37) indicating that on average, children's networks included the same number of speakers of two different languages. To assess whether Language Entropy had an effect on PT, a similar model was run to the Network Size analysis. The Explicit PT score was the dependent variable. Trial Type and Language Entropy were included as fixed effects and Subject was included as a random effect. In a model with Explicit PT as the dependent variable, there was the same significant effect of Trial Type ($\beta = .24$, $p < .05$), but no significant effect of Language Entropy ($\beta = -.04$, $p > .05$) and the interaction was not significant ($\beta = -.11$, $p > .05$; Figure 38). There was no evidence that Language Entropy was related to Explicit PT performance. An identical analysis was performed to test the effects of Language Entropy on Implicit PT performance. The model revealed a null result. There was no significant effect of Trial Type ($\beta = -0.05$, $p > 0.05$) or Language Entropy ($\beta = -0.02$, $p > 0.05$) and the interaction was not significant ($\beta = 0.06$, $p > 0.05$; Figure 38). There was no evidence that Language Entropy was related to Implicit PT performance.

Summary of Pre-Registered Analyses

The analyses showed that Network Size was related to Explicit PT performance. Children with larger social networks had significantly better Explicit PT skills and there was an interaction between Network Size and Trial Type, such that children with smaller social networks did worse on the Does Not See Trials. There was no evidence to suggest that Network Size was related to Implicit PT performance. The Network Size findings with Explicit PT were in line with the adult work - children with larger social networks performed better on the difficult trials in the PT task. The Language Entropy analyses revealed null results across both Explicit and Implicit PT; there was no evidence that Language Entropy was related to PT performance. While prior work suggested that children with more diverse language exposure would have performed better on the PT task, there was no evidence to suggest that is true in the sample.

One reason why this study did not conceptually replicate previous work on linguistic diversity could be that diversity might have a different effect on PT for children in different sized networks. For example, linguistic diversity might differentially affect PT if that diversity is spread out amongst 5 people versus 15 people. To explore this possibility, an exploratory analysis was performed to test whether Network Size and Language Entropy together related to PT. This exploratory analysis focused on Explicit PT only as there were no effects of the social network properties on Implicit PT.

Exploratory Analysis: Network Size, Language Entropy, and Explicit PT

Before exploring how Network Size and Language Entropy interact to affect PT performance, a correlation was run to see whether and how Network Size and Language Entropy were related to each other. There was no evidence that Network Size and Language Entropy were correlated (*rho* = 0.29, $p > 0.05$; Figure 39). A linear mixed effect model was conducted with Subjects as a random effect and Trial Type, Network Size, and Language Entropy as fixed effects. Consistent with the pre-registered analyses, the model revealed a significant main effect of Trial Type ($\beta = 1.77$, $p < 0.001$) and Network Size ($\beta = 0.23$, $p < 0.01$) and no significant main effect of Language Entropy ($\beta = -0.26$, $p > 0.05$). Children did better on Can See than Does Not See trials and children in larger networks had better Explicit PT performance. There was no significant interaction between Network Size and Language Entropy ($\beta = 0.04$, $p > 0.05$), but the interaction with Trial Type and each network variable was significant (Network Size x Trial Type: $\beta = -0.46$, $p < 0.001$; Language Entropy x Trial Type: $\beta = -1.26$, $p < 0.01$). Consistent with the pre-registered analysis, there was marginal evidence that children with smaller networks performed worse on the Does Not See Trials than children with larger networks ($r = 0.40$, $p = 0.057$), whereas there was no relation with performance on the Can See trials and Network Size ($r = -0.13$, $p > 0.05$). Post-hoc FDR corrected correlations were performed to explore how Language Entropy was related to Explicit PT for each Trial Type. The correlations were not significant after correcting for multiple comparisons.

Finally, the 3-way interaction between Network Size, Language Entropy, and Trial Type was significant ($\beta = 0.34$, $p < 0.01$). To explore the nature of this interaction, children were median-split by “small” or “large” social networks (Median Network Size = 12). Post-hoc FDR corrected correlations revealed that for children in small networks, there was a negative correlation with Language Entropy and Explicit PT for the Can See trials – children with more Language Entropy did worse on the Explicit PT task for the Can See trials ($r = -0.60$, $p < 0.05$; Figure 40). Taken together, there is weak evidence to suggest that children in large social networks performed well on the task regardless of Language Entropy levels and across Trial Types. When children in small networks had higher levels of Language Entropy, they performed worse on the Can See trials. This suggests that small, linguistically diverse networks may negatively affect children’s ability to consider others’ points of view, particularly on the more straightforward Can See PT trials.

Discussion

The study provided evidence that different properties of children's social networks are related to their ability to consider others' visual perspectives. Specifically, the number of people in children's network and the diversity in languages spoken by those people related to children's perspective-taking performance. The main finding shows that children in larger social networks performed best on this PT task. Unless they were in larger networks children particularly struggled to consider items outside of their partner's view. Interestingly, the size of and linguistic diversity in children's network together related to children's PT abilities: Children in large networks performed well on the PT task regardless of the different languages spoken by people in their network, but children in small networks only did well on the easier PT trials if they were in more linguistically homogenous networks. Thus, children demonstrated better ability to consider another's point of view when they were either exposed to more people, or were exposed to fewer people who all spoke the same language.

The finding that larger networks relate to better PT skills supports the prediction generated from a network perspective as well as the hypothesis generated from the Social Brain Hypothesis; children who interact with more people on a regular basis have superior PT skill, particularly in challenging PT situations. Interestingly, research with adults and monkeys even suggests a causal link between social skills and social networks: the "social brain hypothesis" proposes that the social environment is determined by the skills of an individual (Barrett et al., 2003; Bickart et al., 2011; Dunbar, 1998; Sallet et al., 2011; Stiller & Dunbar, 2007). These studies suggest that individual differences in PT skill influence the social network that an adult will have. In the current study, it is impossible to assess the directionality because it is a correlational study. While it cannot be known whether better PT skills lead to a larger social network or vice versa, it is true that children's social worlds are much more constrained by external factors than those of adults. While adults have autonomy in who is included in their social network, children have relatively little autonomy. Children's early social networks are largely dictated by parent childcare decisions. As such, this raises the interesting possibility that changes in early social experience may drive children's social cognitive development . Still, children's individual differences may influence their social environment. For example, parents of shy children may be less likely to put their child in situations where they often come into contact with new people. Nevertheless, considering the directionality of the relation between social environment and children's social cognitive development is an interesting area for continued research.

Children in large networks not only have more practice using their PT skill, but they also have more experience using this skill with different kinds of people. As adults' networks get larger, they tend to include more "weak ties," or people in the network with whom the individual is not as emotionally close (e.g., Hill & Dunbar, 2003; Roberts et al., 2009). This is true for children as well: Prior work has shown that as network size increased, the proportion of relations that are "high intense" decreased (Chapter 1), and the same pattern is observed in this sample (see Supplementary Materials), suggesting that when children are in larger networks, they also have more weak ties. Children in large networks may have more experience employing their PT skill when talking to members outside their immediate family and people with whom they are less familiar. It is possible that practice considering the perspective of these distal people enhances children's PT skills, as opposed to considering the perspective of only immediate family members. Children in large networks have more practice, but they also have a more diverse set of people to practice their PT skill with; children in small networks may have fewer opportunities to practice taking the perspective of a more diverse set of people.

Network Size is not a dimension of social experience that developmental psychologists typically measure or explore when they describe early social experience. This study highlights that Network Size is an important dimension of early social experience and it is a dimension that should be explored further. The results showed that Network Size was correlated with PT skill, but it might also be related to other social cognitive skills more broadly, including communication skills, turn-taking, or false-belief understanding and theory of mind.

In addition to the overall effect of network size on PT, the language diversity findings suggest that the number of languages spoken by people in children's networks might have a different impact on cognition depending on the size of a child's social network. In particular, children in small networks with high linguistic diversity performed worse when considering what their social partner could see. Although prior work suggested that high linguistic diversity would benefit PT (Fan et al., 2015; Liberman et al., 2016), the results reported here show linguistic diversity may in fact have negative relations with PT under certain circumstances. Indeed, for a child in a small network, high levels of linguistic diversity could potentially be confusing. Imagine that a child interacts with 4 people on a regular basis, but each person speaks a different language. These interactions could be very difficult to navigate, especially if the child does not speak all of those languages. If instead a child has 16 people in their network and 4 people speak different languages, this diversity may be beneficial for the child without being too complex. Although in both cases the same number of people speak different languages, the combination with network size may jointly determine an optimal level of linguistic diversity. Though linguistic homogeneity may be beneficial for children in small networks, linguistic diversity may still be an important predictor of PT overall. One might speculate that with a certain minimal level of linguistic homogeneity, linguistic diversity can become beneficial.

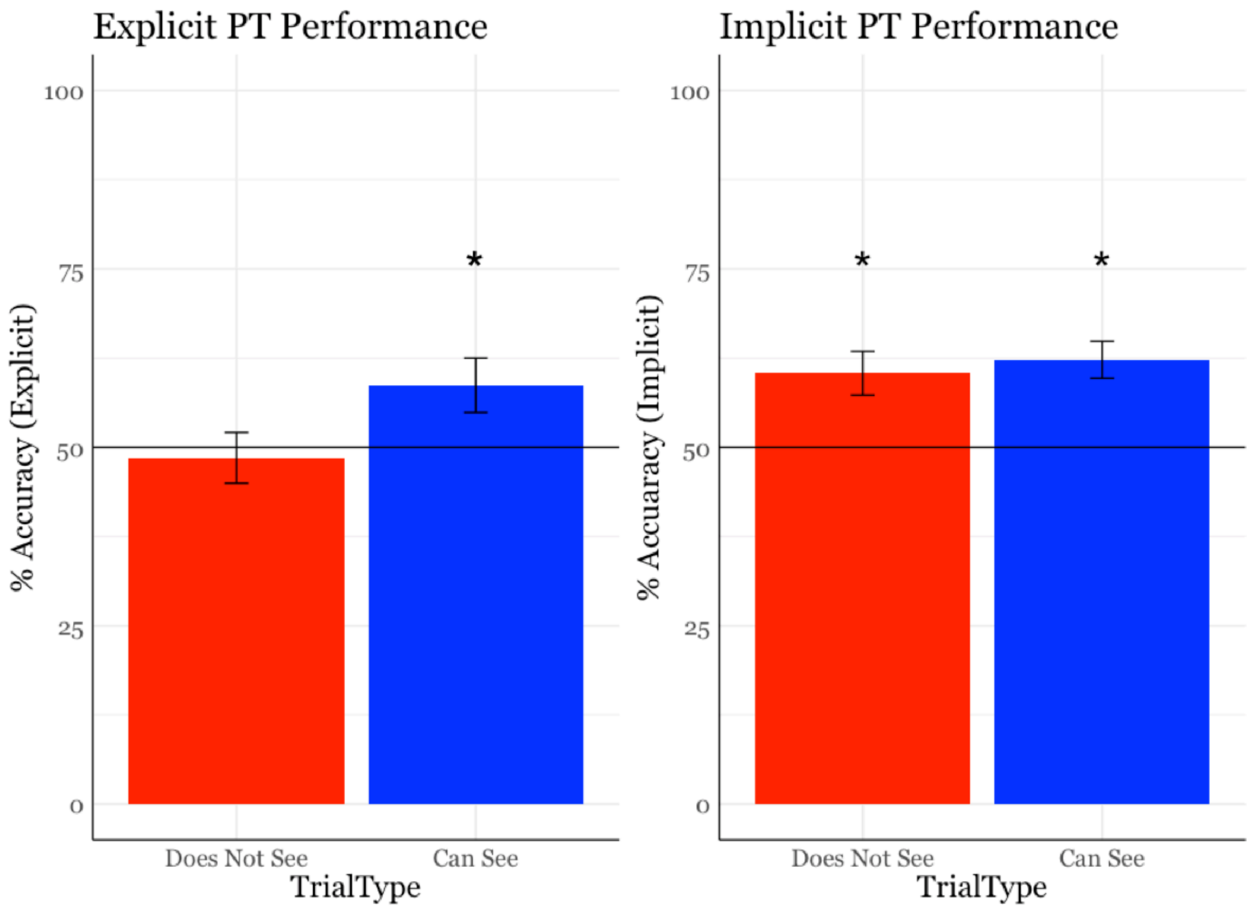
Also, one possible reason why there was not a positive relation between linguistic diversity and PT is that the sample was different from that of prior work. Most of the children and parents in the sample were monolingual English speakers because a prerequisite for inclusion in the PT study was high proficiency in English. Prior research included participants with more diverse language backgrounds. It is possible that if the participants were more linguistically diverse themselves, it would have been possible that children with more linguistic diversity in their network performed better on the PT task. In addition, the measure of linguistic diversity did not test children's exposures to different languages directly. Parents reported the number of languages each member of the child's network spoke; the demographic form did not specifically ask whether they spoke each language to the child. Presumably, if parents know someone in their child's social network speaks a language other than English, they have likely heard that person speak that language. This suggests their child has probably heard that person speak another language, but that cannot be discerned that from the data. Future work could specifically ask about languages spoken to the child to see if Network Linguistic Diversity looks different for preschool children.

In addition to being mostly monolingual speakers, the sample was mostly of high socio-economic status (SES). It is important to test a more socio-economically diverse sample to see if the same patterns are observed. In the adult social network literature, differences are observed in network size for low- and high-SES adults; adults from high-SES backgrounds have less closely knit networks and fewer family members are represented in their network (Campbell et al., 1986; McPherson et al., 2005). There are different theories that suggest people who are high- versus low-SES have different functions for the ties in their network, which could explain these differences. High-SES individuals do not need to rely on individuals outside of the home for the economic security of their household; they can afford to have less closely knit networks and networks that have more weak ties (Granovetter, 1983). Given these differences in adults, it is important to explore both the structure of networks for children of lower-SES backgrounds and whether experience relates in the same way for social cognitive development.

In summary, this study used a novel method, *The Child Social Network Questionnaire*, to capture and describe children's early social experience in relation to children's ability to consider another's perspective. The findings suggest that variation in early social experience is related to PT in young children; particularly, children in larger social networks had better PT skills. This effect was especially visible in more difficult visual perspective situations, like when the child saw an object their partner could not see. Further, for children in smaller social networks, those who had less linguistic diversity in their network had improved PT performance. Overall, these results indicate that both the size of and linguistic diversity in children's social worlds relate to their ability to consider things from another person's point of view. Importantly, this study highlighted the importance of using social networks to explore how variations in early social experience relates to social cognition. Social networks will allow developmental psychologists to explore other dimensions of early social experience that might be important for social cognitive development with greater precision to measure aspects of diversity in children's social worlds. By utilizing novel social network analysis techniques, this study found important relations between the structure and makeup of children's social worlds and the social skills children use to navigate their social world.

Figure 31

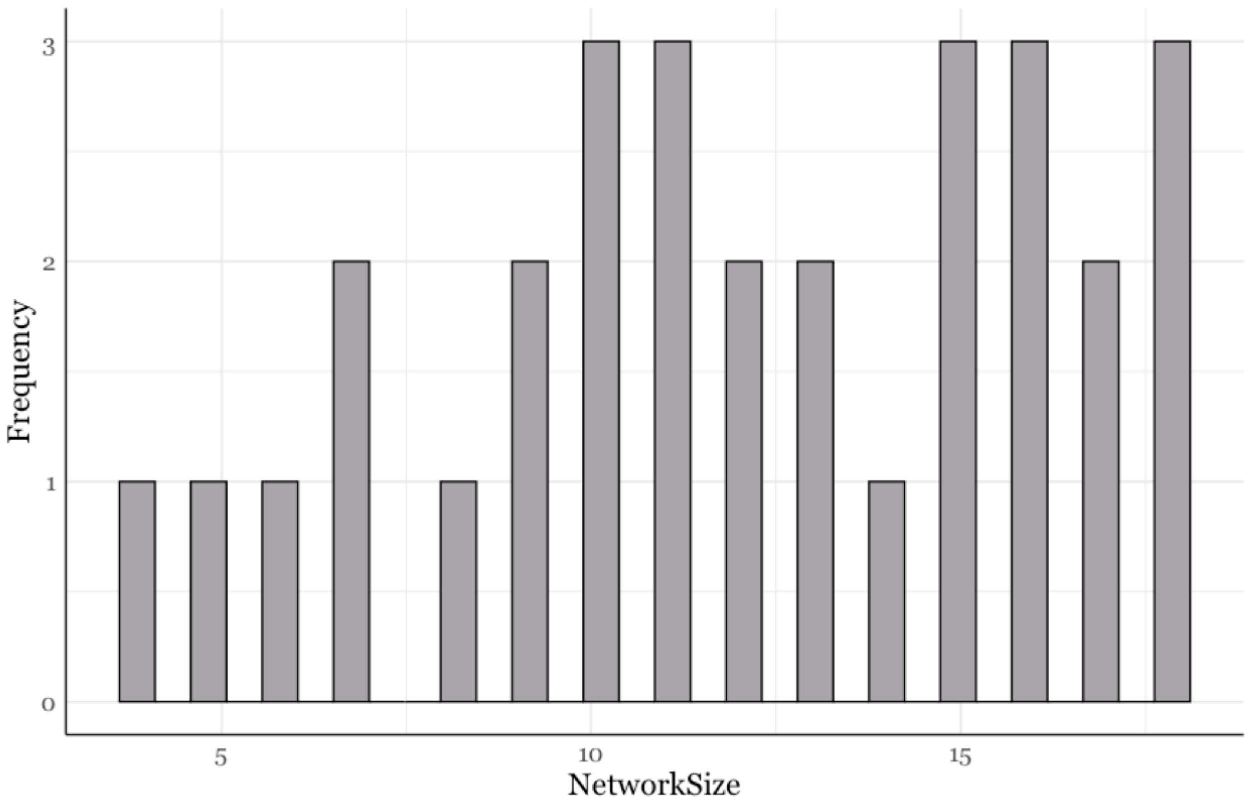
Performance on Explicit PT and Implicit PT



Note. Follow-up t-tests with FDR corrections confirm that for Explicit PT, children performed above chance for the Can See Trials ($M = 0.59$; $t(29) = 2.40$, $p < 0.05$) and they did not perform above chance for the Does Not See Trials ($M = 0.49$; $t(29) = -0.09$, $p > 0.05$). For Implicit PT, children performed above chance for Can See Trials ($M = 0.61$; $t(29) = 4.39$, $p < 0.001$) and for Does Not See Trials ($M = 0.57$; $t(29) = 2.66$, $p = 0.01$).

Figure 32

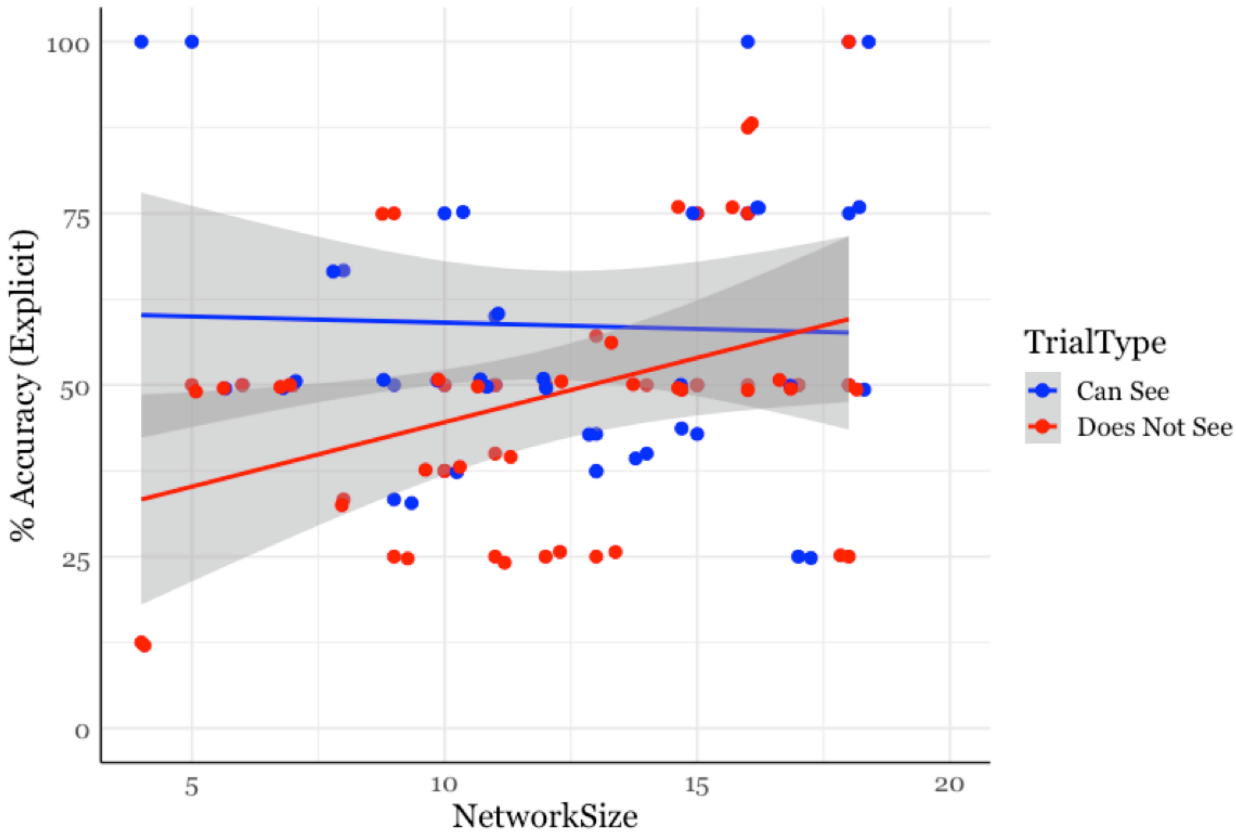
Histogram of Network Size



Note. Children have an average Network Size of 12 people (*SD* = 4.01).

Figure 33

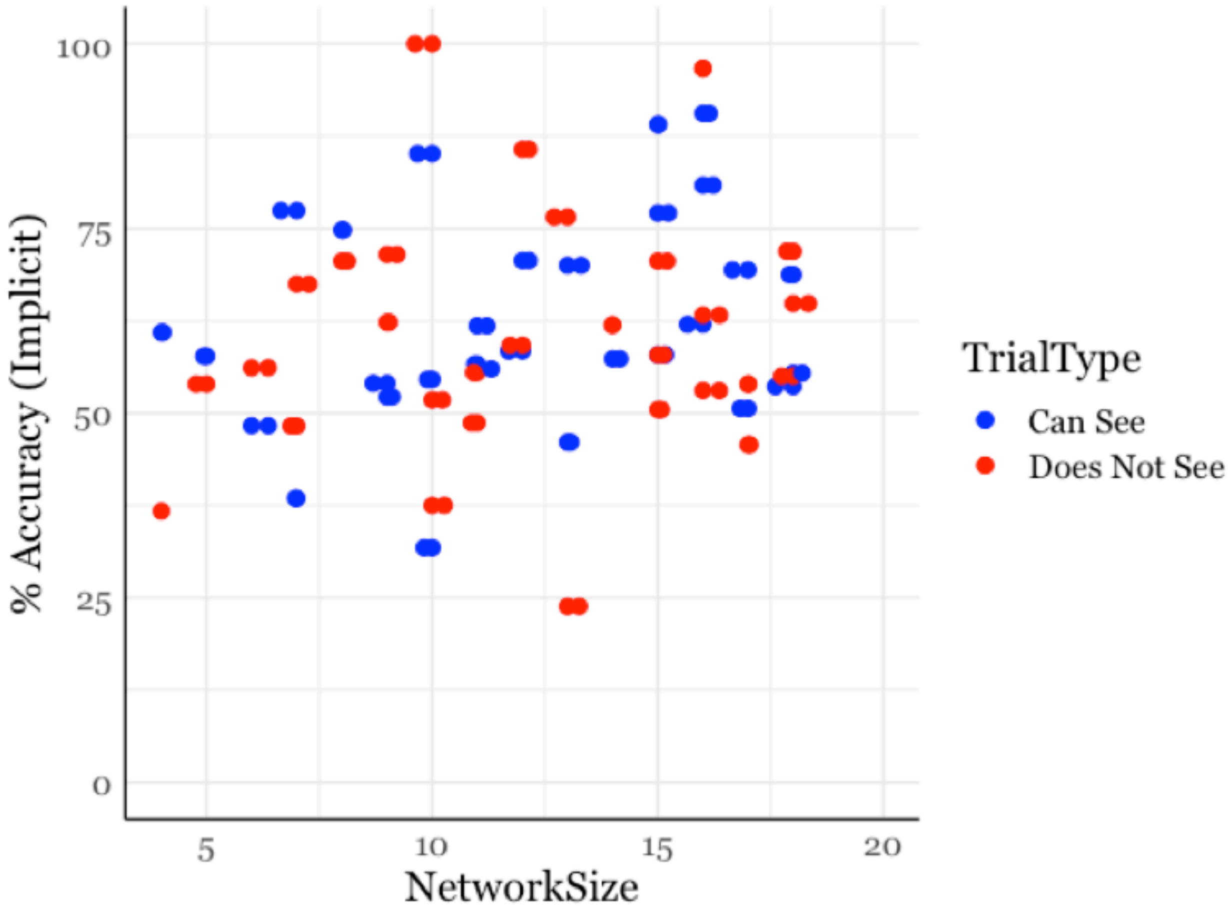
Network Size and Explicit PT



Note. The model revealed a main effect of Trial Type ($\beta = 0.89$, $p < 0.01$), a main effect of Network Size ($\beta = 0.15$, $p = 0.05$) and a significant interaction between Trial Type and Network Size ($\beta = -0.22$, $p < 0.05$).

Figure 34

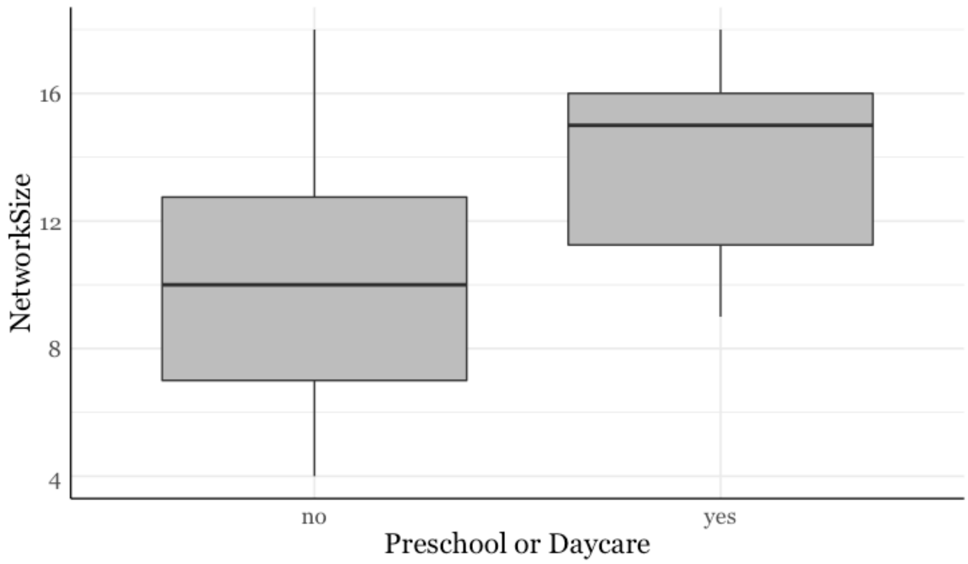
Network Size and Implicit PT



Note. The model revealed null results. There was no evidence that Network Size was related to Implicit PT performance.

Figure 35

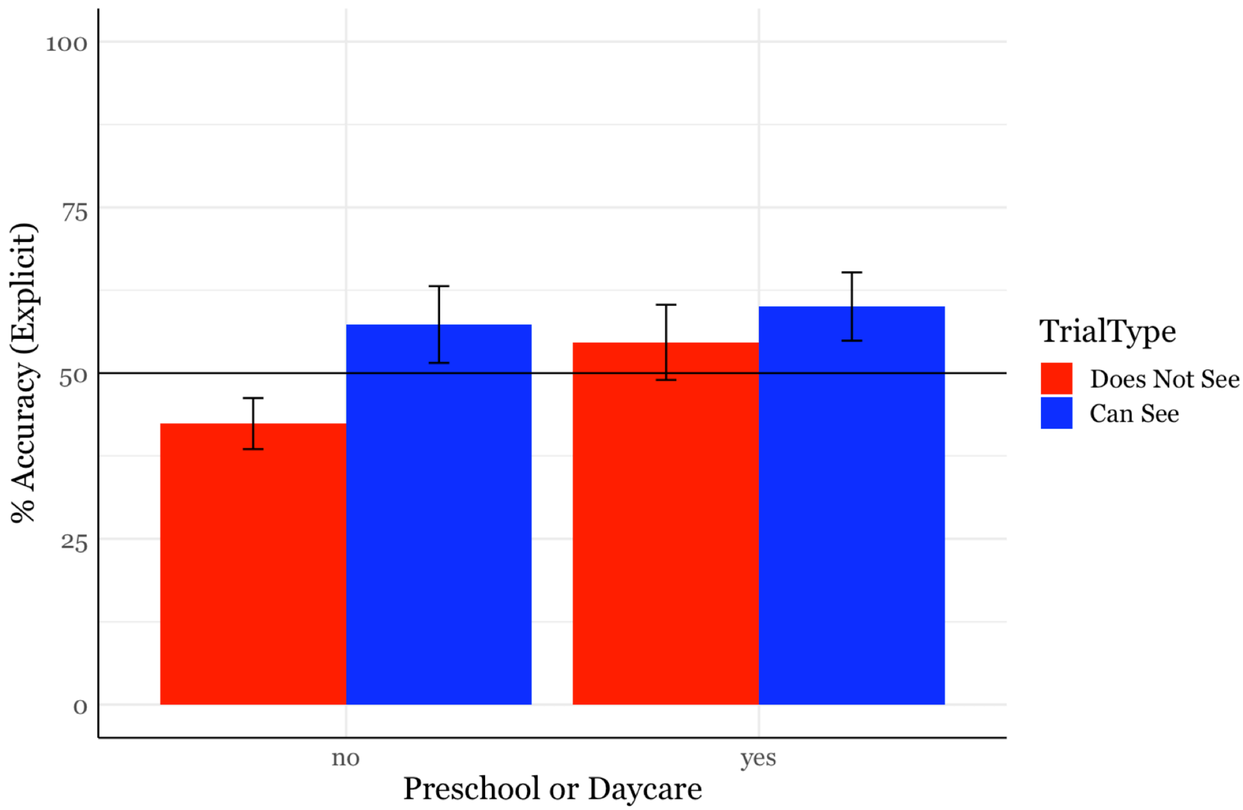
Network Size and Preschool/Daycare



Note. Children in Preschool or Daycare have significantly larger networks than children who are not in Preschool or Daycare ($M_{Preschool}$ = 14 people, $M_{NoPreschool}$ = 10 people; $t(23) = -2.94$, $p < 0.01$).

Figure 36

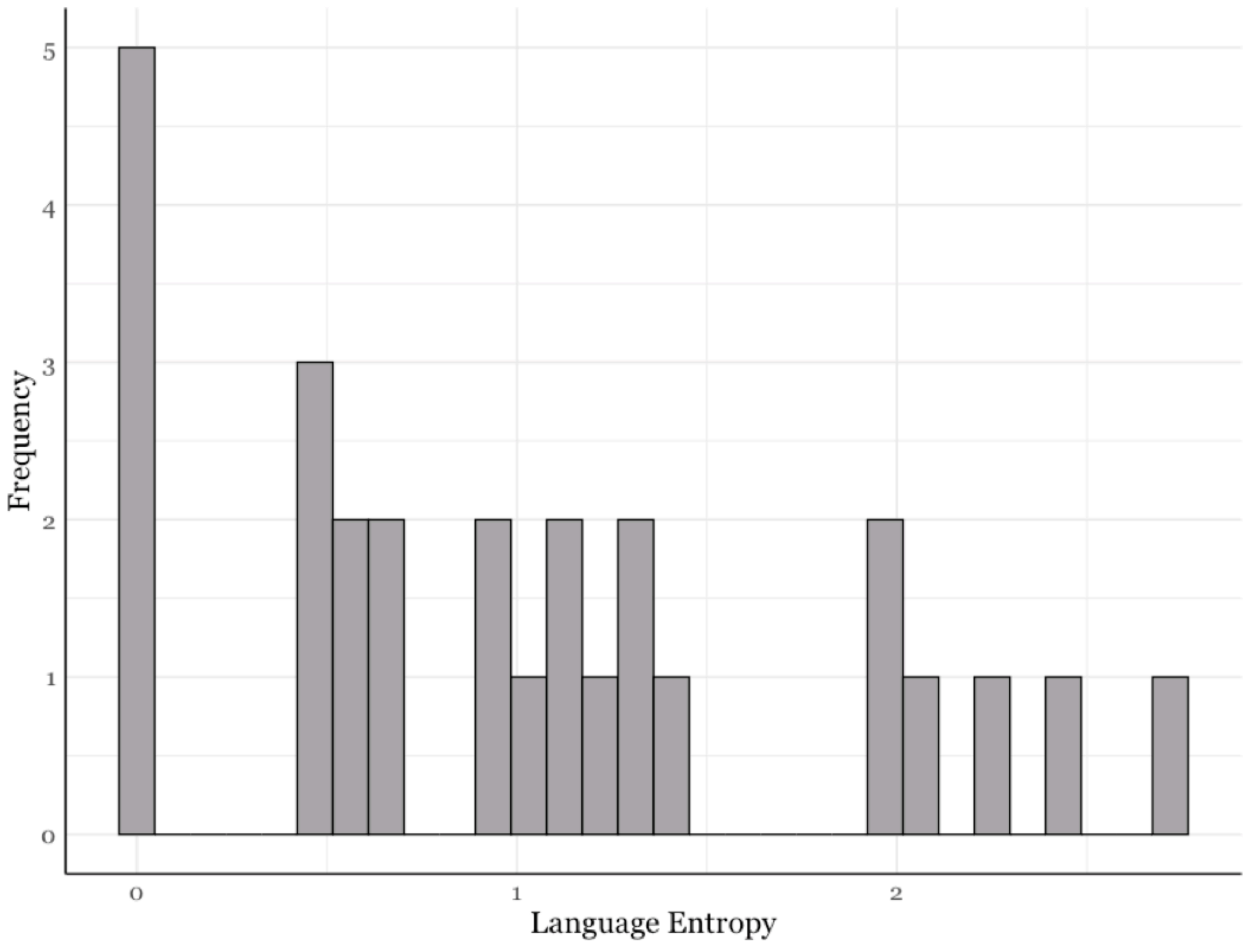
Preschool/Daycare and Explicit PT



Note. The model revealed a significant main effect of Trial Type consistent with the previous models ($\beta = 0.19$, $p < 0.05$), but did not reveal a main effect of Daycare ($\beta = 0.15$, $p > 0.05$) or an interaction ($\beta = -0.12$, $p > 0.05$). There was no evidence that School experience was related to Explicit PT performance.

Figure 37

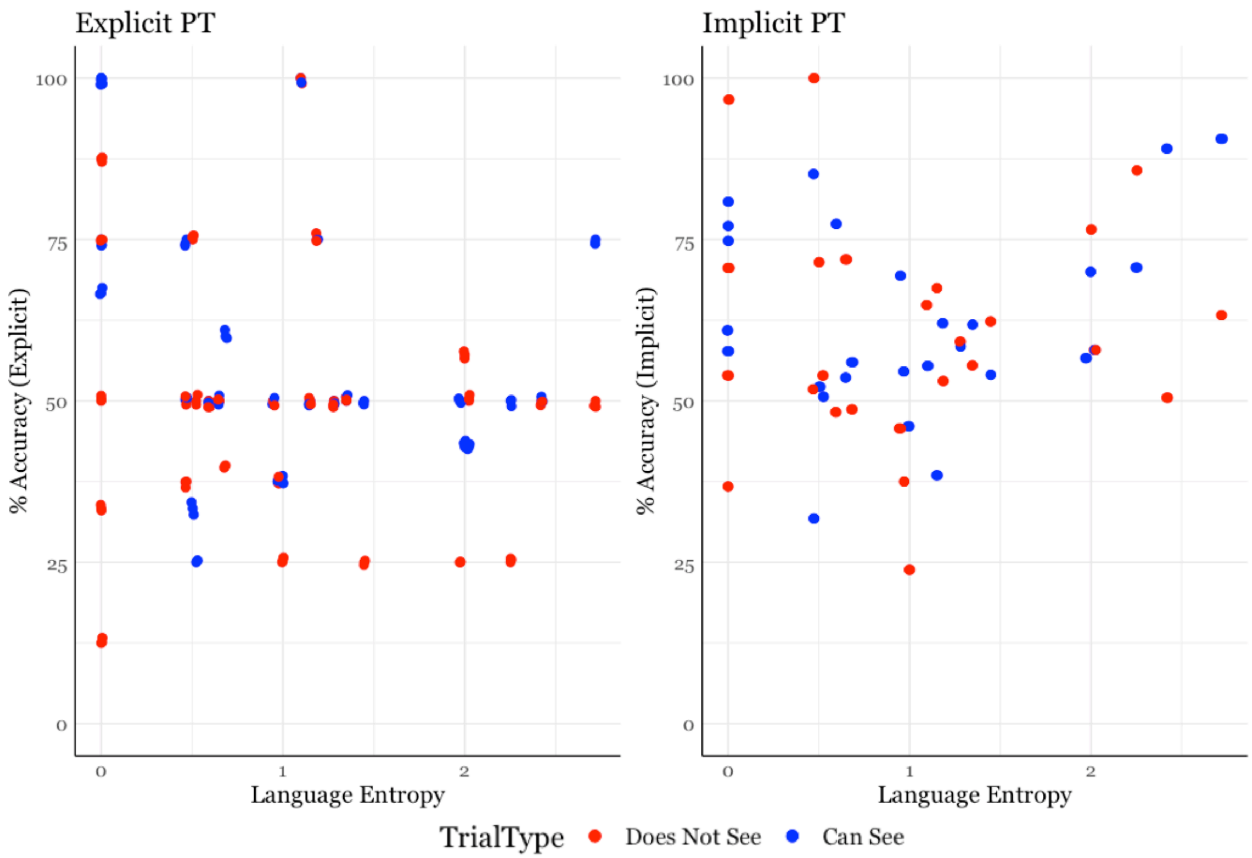
Histogram of Language Entropy



Note. Language Entropy was calculated using the egor package (Krenz et al., 2020).

Figure 38

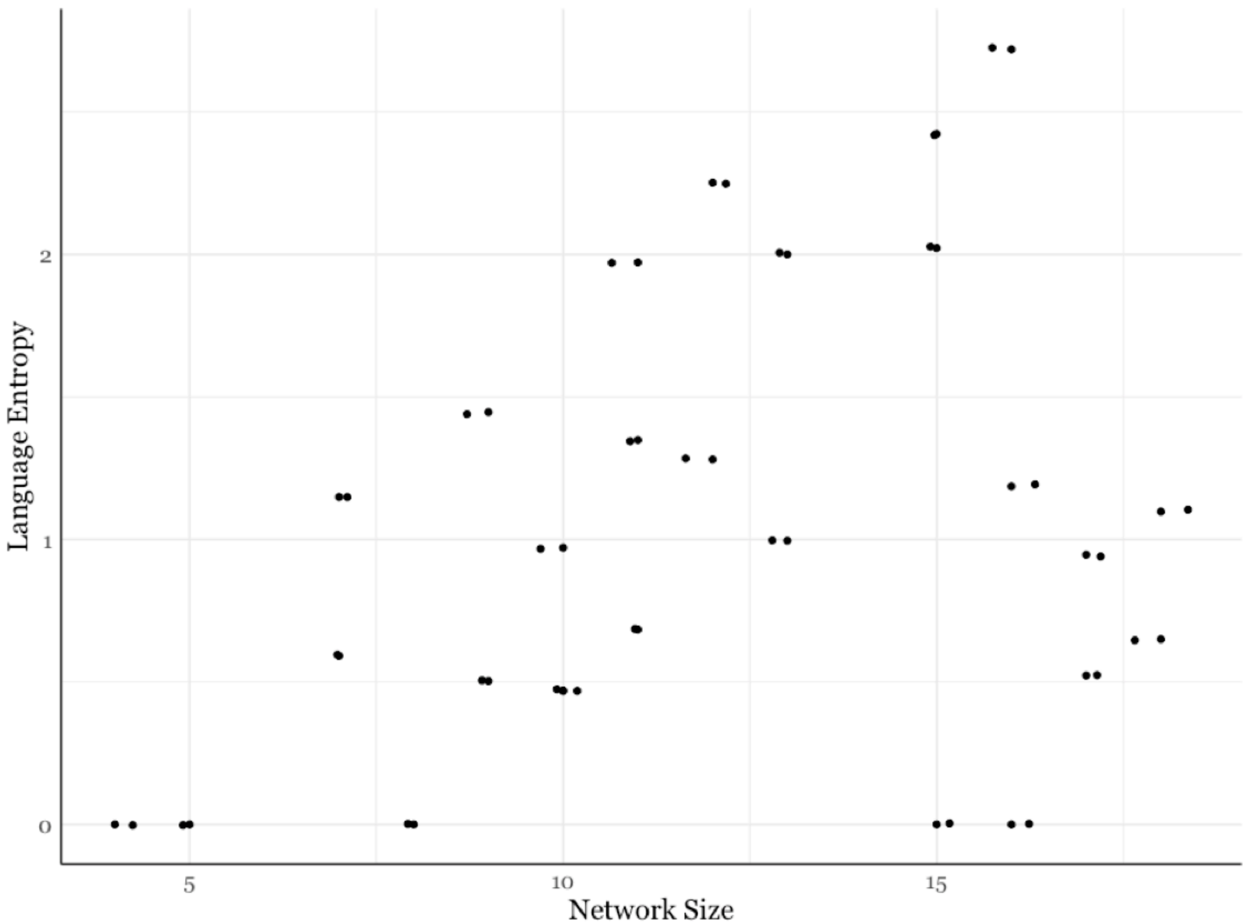
Network Language Entropy and PT



Note. There was no evidence that Language Entropy was related to either Explicit PT or Implicit PT performance.

Figure 39

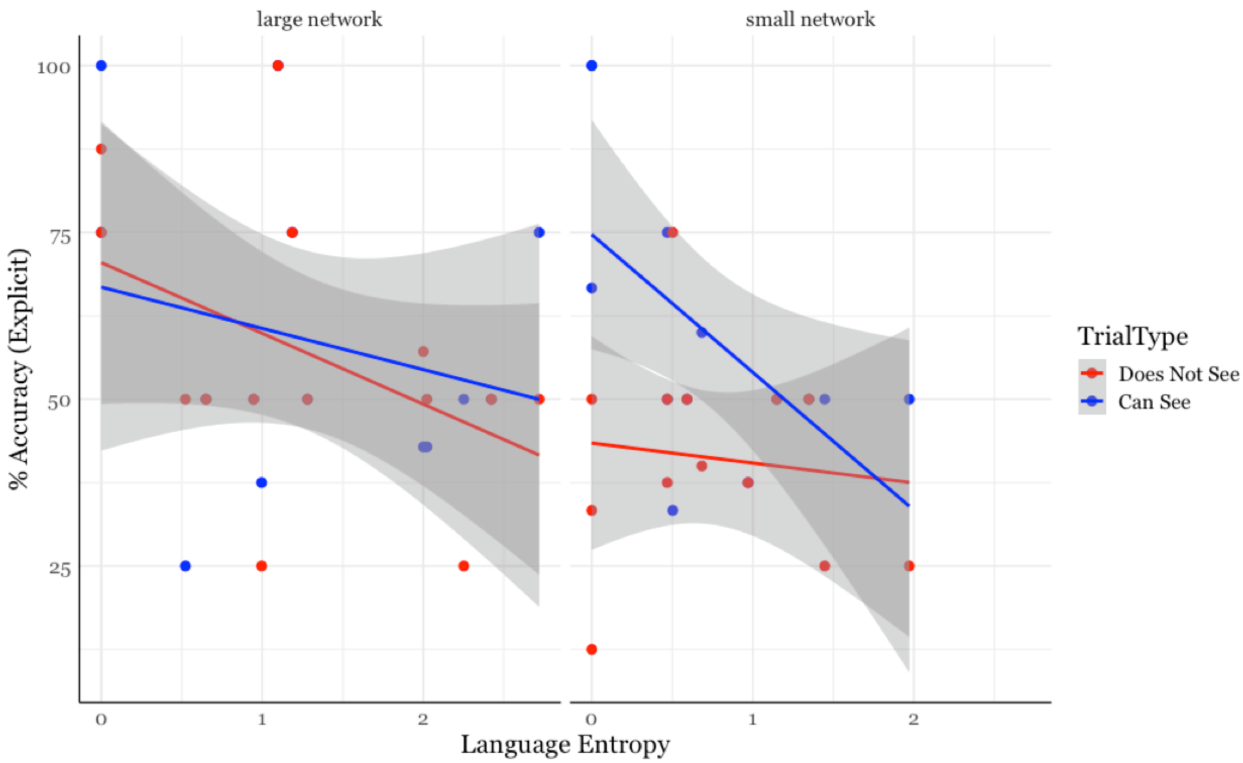
Correlations between Network Size and Language Entropy



Note. There was no correlation between Language Entropy and Network Size (*rho* = 0.29, *p* = 0.15); however, the scatterplots demonstrate that there are no participants with high Language Entropy in small social networks.

Figure 40

Network Size, Language Entropy, and Explicit PT



Note. A large network child was someone who had 12 or more alters in their social network.

Chapter 2 Supplemental Materials

Further Description of the PT Task

Below is a further description of the behavioral PT Task as described in Brezack et al. (in press).

Procedure

The *Familiarization with Experimenter Perspective* phase introduced the child to E1's perspective on the toys. The child was shown the apparatus from E1's point of view. E1 narrated while the child saw that when each door was opened, one toy at a time could be viewed. Then the child returned to his or her side of the table for the remainder of the study. In the *Introduction* phase, E1 explained the task cover story and allowed the child familiarity with the voiceover animal prompts. E1 introduced herself to the first animal friend, invited the child to do the same, and encouraged the child to help the animal find his toys. E1 then affixed the animal card to the barrier. To contrast E1's perspective with that of the child, the *Perspective Practice* phase allowed the child to experience the setup from his or her own perspective with a procedure analogous to *Familiarization with Experimenter Perspective*. Audio prompts narrated the child's and animal's shared perspectives to clarify that the child's view differed from E1's: The child and animal friend can see both toys at all times while E1, with only one door open, can see one toy at a time.

Test Trials

Children then participated in as many as four blocks of Test Trials with 8 trials per block in the same fixed order across participants. Blocks 1 and 3 were PT blocks, and 2 and 4 were Control trial blocks. Between each block was a Catch Trial designed to ensure the child was still paying attention.

For each Test Trial and Catch Trial, E2 simultaneously placed two identical toys (or different toys in Catch Trials) on the platform, one on each colored mat. This occurred while both doors were closed so E1 could not see the toys and the barrier was raised to prevent the child from manipulating toys. Then, E1 opened one door (or both doors during Catch Trials), greeted the child, and played the audio prompt in which the animal requested one of the two toys dependent on the *Trial Type* (Figure 2). E1 waited two seconds following the end of the audio prompt, during which children's eye gaze (implicit response) was later coded via a webcam mounted under the platform. E1 then lowered her hand, saying, "Can I have it?" while E2 simultaneously lowered the barrier so the child could choose a toy to hand to E1. Once the child handed a toy, E1 placed the toy in the box behind her. If the child handed both toys, E1 indicated that one toy should be given. She encouraged reluctant children to hand her a toy and replayed the audio prompt if necessary until the child handed a toy. Within each block, the open door side and the correct response side (the child's left or right) were counterbalanced. The same toys used in PT blocks were used in Control blocks.

Linguistic EI Index and PT

Linguistic EI Index

EI Index is a measure of homophily the child shares with the network. "E" stands for external or different alters and "I" stands for internal or same alters. Each alter is categorized as either "same" or "different" from the child based on some attribute and is calculated as follows: *(Number of Different Alters – Number of Same Alters)/Network Size* (Krackhardt & Stern, 1988; Krenz et al., 2020). The EI Index ranges from -1 to 1; a score of -1 indicates the entire network is the same as the child on some attribute and a score of 1 would indicate that the entire network is different from the child on some attribute. For the Linguistic EI Index, each alter was coded as same-speaker or different-speaker. For monolingual English children, this meant anyone who spoke a language other than English was coded as different-speaker. For bilingual and multilingual children, an alter was coded as different-speaker if that person spoke a language the child did not speak or hear from their parent. For example, imagine an English/Spanish bilingual child with a network where 2 people spoke English, 1 spoke English and Spanish, and one spoke English and Dutch. The only alter that is a different-speaker is the English/Dutch bilingual because the child does not speak Dutch and would therefore have a Linguistic EI Index of -0.5 ([Different-speaker – Same-speaker]/Network Size; [1 – 3]/4).

Linguistic EI Index and Perspective-Taking

Children's Linguistic EI Index was on average -0.70 (*SD* = 0.32, range = -1 - 0.08). A histogram of the 3-year-olds' Linguistic EI Index is presented below. To assess whether Linguistic EI Index had an effect on PT, a Linear Mixed Effect model was performed analogous to the analysis for Network Size. The Explicit PT score was the dependent variable. Trial Type and Linguistic EI Index were included as fixed effects and Subject was included as a random effect. The model revealed null results; there were no main effects of Trial Type ($\beta = 0.04$, $p > 0.05$) or Linguistic EI Index ($\beta = 0.006$, $p > 0.05$) and the interaction was not significant ($\beta = -0.13$, $p > 0.05$). There was no evidence that Linguistic EI Index was related to Explicit PT performance. This does not conceptually replicate previous work that children with more multilingual experience are better at PT (Fan et al., 2015; Liberman et al., 2016). While we should exert caution in interpreting a null result, there is no evidence that Linguistic EI Index is related to Explicit PT performance.

The same model was performed to test the effect of Network Linguistic Diversity with Implicit PT as the dependent variable. Similar to Explicit PT, the model did not show a main effect of Trial Type ($\beta = 0.13$, $p > 0.05$) or Network Linguistic Diversity ($\beta = -0.02$, $p > 0.05$), and there was no significant interaction ($\beta = 0.17$, $p > 0.05$). Thus, there is no evidence that Network Linguistic Diversity was related to Implicit PT.

Figure 41

Histogram of Linguistic EI Index

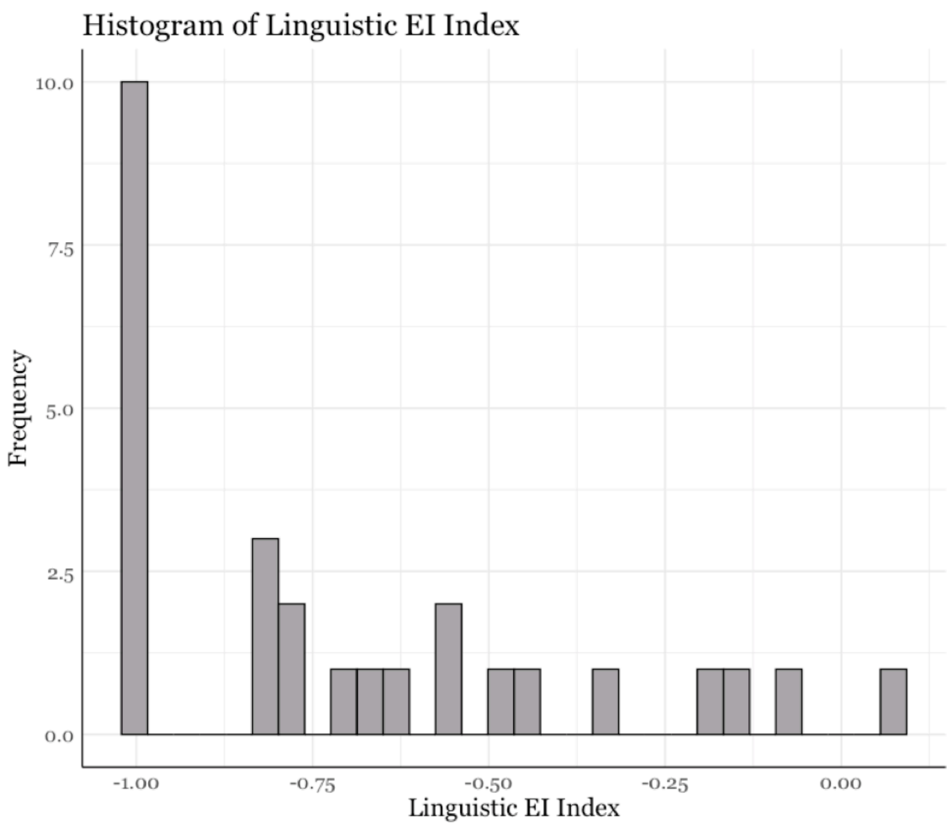
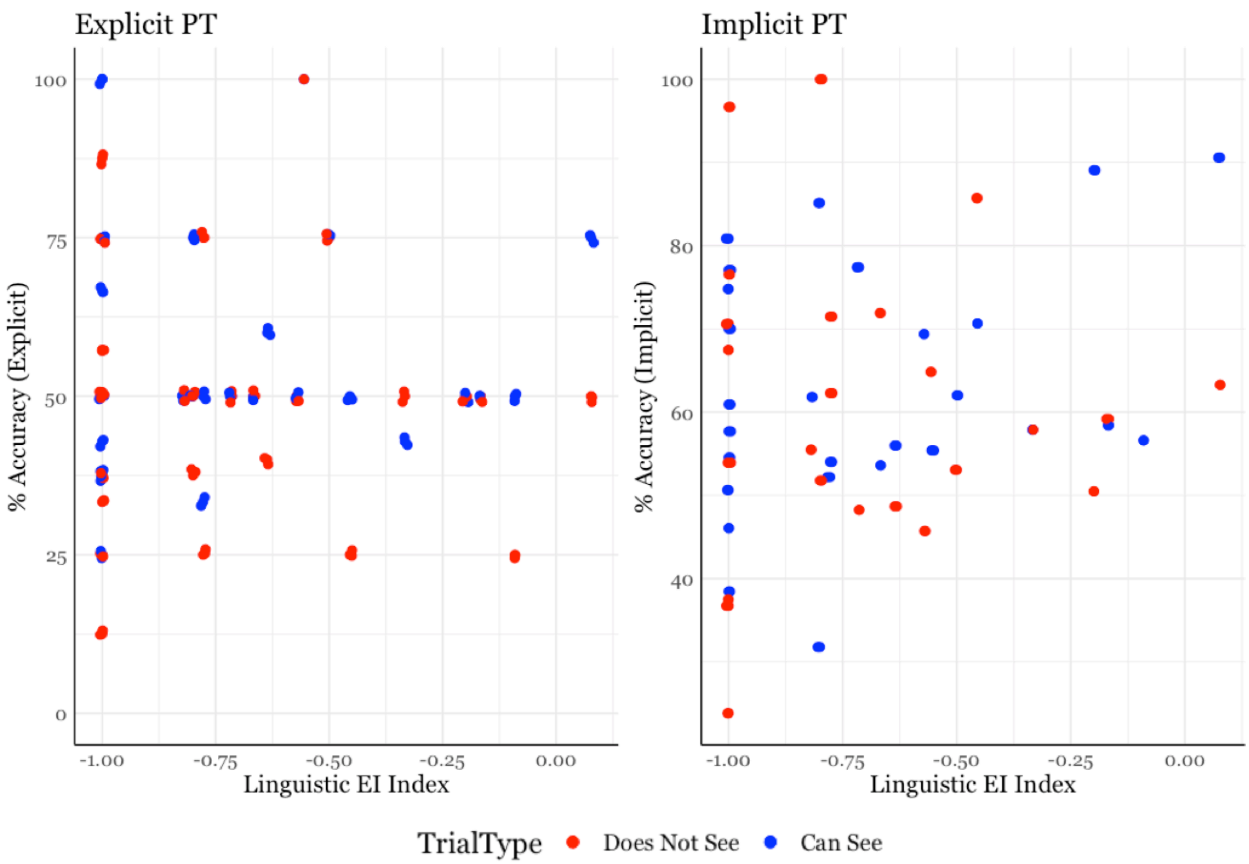


Figure 42

Linguistic EI Index and PT



Language Entropy

The following discrete language categories were used to calculate Language Entropy.

Each alter in the child's social network was a speaker of one of the following categories:

- English only
- English/Spanish
- English/Dutch/French/German
- English/Chinese/Spanish
- English/Eastern European Language
- Spanish only
- English/Spanish/Russian
- English/Chinese
- English/French
- English/Hebrew

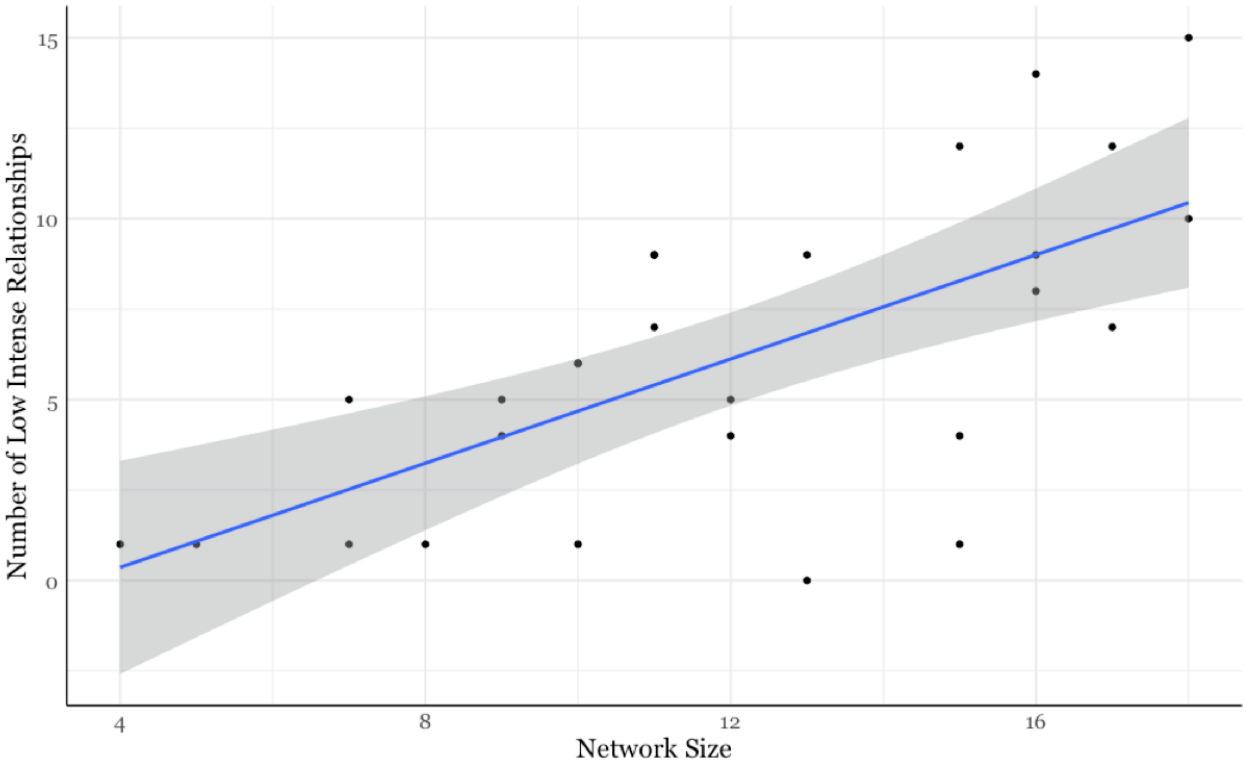
- English/French/Russian/Romanian
- English/Chinese/Hebrew/Spanish
- English/Arabic
- English/Arabic/Mandarin/Spanish
- English/Balinese/Indonesian
- English/Malayalam
- English/American Sign Language
- Preverbal
- English/Yoruba
- English/Cantonese/Mandarin
- English/Mandarin
- English/Korean/Spanish
- English/Russian/Ukrainian
- English/Russian
- English/Ukrainian
- English/French/Spanish
- English/Bengali
- English/Russian/Uzbek/Turkish/Persian
- English/Polish
- English/American Sign Language/Spanish
- Russian/German/Spanish/Chinese
- German/Russian
- English/Korean

Network Size and Weak Ties

There were three measures to assess the intensity of the relationship: the number of activities the person does with the child, how emotionally close parents reported their child feels toward the person, and the proportion of waking hours the person spends with the child (see Appendix A). A z-score was calculated across all relationships for each of the three measures and an average z-score was computed for each relationship. A median split of the average z-score then classified each relationship as either "low" or "high" intensity. The figure presented below demonstrates that as Network Size increases, so does the number of low intense relationships ($r = 0.63$, $p < 0.001$).

Figure 43

Number of Low Intense Relationships increased with Network Size



Additional Network Properties and Explicit PT

Below are additional analyses we conducted to explore how other properties of children's social networks might relate to PT. All the models were Linear Mixed Effects models that had Subjects as a random factor, Trial Type as a fixed factor, and the network variable of interest as a fixed factor. Explicit PT was the dependent variable. We focused our supplemental analyses on Explicit PT because this is where we saw effects for our pre-registered analyses.

Calculation of Additional Network Properties

Using *The Child Social Network Questionnaire* we could also calculate the following network properties for each child: Proportion of Low Intense Relationships, Proportion Adult

Relationships, Proportion Kin Relationships, Component Ratio, Number of Components, and Number of Friends.

Proportion of Low Intense Relationships

See the previous section "Network Size and Weak Ties" for a description on how the intensity of the relationships was measured. Once relationships were categorized as either high or low intense, the proportion of low intense relationships was simply: *Number of Low Intense Relationships / Network Size*.

Proportion Adult Relationships

Each alter in the social network was classified as "adult" or "child". A child was anyone 12-years-old or younger consistent with Chapter 1. The proportion of adult relationships was calculated as follows: *Number of Adults / Network Size*.

Proportion Kin Relationships

Each alter in the social network was classified as either "kin" or "not kin"; kin was any individual in the immediate or extended family (e.g., grandparents, aunts, uncles, cousins, etc.). The proportion of kin relationships was calculated as follows: *Number of Kin / Network Size*.

Number of Friends

A friend was any named peer alter of the child. In this sample, children had an average of 2.5 friends (range: 0 – 10).

Number of Components

Components are a way to describe the structure of the network. A component emerges in the network when all the alters are connected to each other in some way (Perry et al., 2018). In an egocentric network, a component emerges when all the alters are connected even when you remove the child. The number of components are determined from the parent interview. See Chapter 1 for more details. In this sample, children on average had 3.3 components (range: 1-7).

Component Ratio

Another way to describe network structure is to describe how fragmented the network is. The measure to describe how fragmented a network is called the Component Ratio. Larger networks tend to have more components, so to account for network size the Component Ratio can be calculated as follows where C is the number of components: *(C – 1) / (Network Size – 1)* (Perry et al., 2018). Larger values of the component ratio indicate that the network is more fragmented.

Regression Table

Below is a regression table showing the effects of the Network Variable of Interest, Trial Type, and the interaction with Explicit PT as the dependent variable. The models revealed mostly null results. There was no evidence to suggest these other network properties were related to PT.

Table 8

Exploratory Network Variable Analysis and Explicit PT

Network Variable	Network Variable		Trial Type		Interaction	
	ß	*p*	*ß*	*p*	*ß*	*p*
Proportion of Low Intense Relationships	0.22	0.20	0.28	0.08	-0.20	0.32
Proportion of Adult Relationships	-0.20	0.57	0.08	0.81	0.08	0.85
Proportion of Kin Relationships	-0.07	0.63	-0.07	0.66	0.08	0.67
Number of Friends	0.03	0.42	**0.19**	**0.02**	-0.05	0.29
Number of Components	0.09	0.48	0.43	0.14	-0.16	0.29
Component Ratio	0.06	0.81	0.21	0.12	-0.19	0.51

Chapter 3: Does racial diversity impact children's emerging racial bias? Depends on where they live and how their social world is structured

By the time children are in preschool, children from high-status racial groups show strong, explicit in-group favoritism (Aboud & Amato, 2001; Cristol & Gimbert, 2008). Children from low-status racial groups show a pattern of mixed results; some studies find that children from low-status racial groups also show an in-group favoritism (Fox & Jordan, 1973; Hraba & Grant, 1970; Newman et al., 1983), while other studies find that this in-group bias is not as strong as it is for high-status children (Brand et al., 1974; Gregor & McPherson, 1966; Jordan & Hernandez-Reif, 2009; Katz & Zalk, 1974; Kircher & Furby, 1971; Newman et al., 1983; Shutts et al., 2011; Teplin, 1976; Vaughan, 1964). There are even studies that find the opposite pattern – that children from low-status racial groups prefer the high-status group (Asher & Allen, 1969; Greenwald & Oppenheim, 1968; Rohrer, 1977; Spencer, 1984). There is an abundance of prior work that has explored the development of racial attitudes in preschool-aged children (see Hailey & Olson, 2013 for a review); however, very little work has asked about how variations in children's exposure to different races might relate to these intergroup attitudes.

Children's contact with different racial groups is likely not the sole predictor of racial bias in childhood. Racial bias is a multidimensional and multilevel construct; however, prior developmental work suggests that individual differences in exposure to racial diversity might predict some of the variation in racial bias. A handful of studies have found that children in environments with more racial and ethnic diversity are better at racial encoding (Weisman et al., 2015), essentialize race less (Mandalaywala et al., 2019), essentialize ethnic identify less (Deeb et al., 2011), and exhibit less racial bias toward an out-group (Rutland et al., 2005). This prior work suggests that children are sensitive to their social environments; however, these studies used a variety of methods to assess "racial diversity" – a mixture of in-lab questionnaires asking about racial out-group exposure, demographics of the schools children attended, or even demographics of the neighborhoods children live in. Because these studies use a variety of methods to capture "racial diversity" it is not clear which kinds of experiences contribute most strongly to children's racial attitudes. For example, does neighborhood diversity shape children's attitudes independent of their own relationship experience?

Positive contact with minority out-group members often relates to better inter-group attitudes among White Americans, as predicted by Intergroup Contact Theory (e.g., Pettigrew, 1998). Yet, White Americans who live in areas with increasing and greater minority populations report less support for integration and more negative inter-group attitudes, suggesting that members of racial groups treated as high-status sometimes experience increases in the diversity of their neighborhoods as threatening (Craig et al., 2018). These findings illustrate the multiple ways in which different aspects of experiences of diversity can shape inter-group attitudes. Therefore, it remains an open question how early social experience and what kinds of experience are going to relate to children's emerging racial bias. This work with adults highlights why it is problematic to use neighborhood demographics to approximate "typical" experience in early childhood. Different kinds of social experience could have a differential effect on children's emerging racial bias.

Social networks provide a novel, innovative method to assess the diversity of children's close, personal relationships (Chapter 1). The racial diversity of the network can be assessed by categorizing the representation of different races in the network, which has been done in prior work with adults. Among adults and adolescents, the composition of these networks appear to shape identity; for instance, White Americans in large social networks described their ethnic identity as less important to them than those in smaller social networks, and biracial adults whose parents were Black and White identified more strongly with being Black when Black people were more represented in their social network (Rockquemore & Brunsma, 2002). Social network analysis has also been used to explore how the racial composition of a school or community impacts racial segregation and integration, for instance, to document that college students tend to have more same-race friends than different-race friends (Wejnert, 2010) and to examine how neighborhood racial segregation is related to segregated friendship choices in middle and high school students (Mouw & Entwisle, 2006). The present study will harness the power of social network analysis, in combination with neighborhood demographic data, to assess which kinds of early social experience contribute most strongly to preschooler's early emerging racial bias.

The research questions and analysis plan were pre-registered (https://aspredicted.org/blind.php?x=r3jz6f). The broad research question was: How do variations in children's social networks relate to their racial preferences? Specifically, this study will ask: how does Network Racial Diversity, Network Size, Network Structure, and distal neighborhood properties relate to children's pro-White bias? The predictions for the White children are clear and motivated by prior work; White children with more network racial diversity should exhibit less pro-White bias. For Racial minority subjects, it remains an open question how the Network Racial Diversity will impact their pro-White bias. This friendship-choice task measures children's pro-White bias specifically. It remains an open question how the racial make-up of racial minority children's regular social contact will relate to their pro-White bias because this is not a test of in-group preference, but rather, a test of their preference for the racial group viewed as higher status in society. Will the representation of different racial groups also relate to a decrease in the bias, consistent with the prediction for White children? These possibilities are explored below. The analysis would be underpowered to include child race into the models because of the small numbers of Black, Asian, and Hispanic/Latinx subjects, so the data is analyzed using two groups – White subjects and Racial minority subjects. This is not ideal because Racial minority subjects are not a monolith; however, this analysis plan allows for full data retention and will provide insight for future work to answer these questions.

Across all subjects, it remains an open question how Network Size and Network Structure measures will interact with racial diversity measures to relate to children's pro-White bias. A network perspective generate questions such as, does high levels of racial diversity impact children the same in small and large networks? If racial diversity does relate to children's pro-White bias, does it matter how that diversity is patterned in the social network? The present study will not only explore how racial diversity and exposure impacts children's pro-White bias, but it will also explore contextual variation in how racial diversity might impact emerging racial bias.

Method

Participants

Participants were recruited from the Museum of Science and Industry in Chicago, IL. Parents with children who looked to be between the ages of 3- and 4-years-old were approached and asked if they wanted to participate in a science study. 108 3- and 4-year-olds were recruited to participate in the study. 7 participants were excluded due to parents not being able to provide enough detail during *The Child Social Network Questionnaire* for a final sample of 101 subjects who participated in the Racial Preference Task (M_{age} = 48.16 months, males = 51, females = 50). 51 were White or European-American, 27 were Biracial, 9 were Black or African-American, 7 were Asian or Asian-American, 5 were Hispanic or Latino-American, and 2 reported Other. While children participated in the Racial Preference Task, parents participated in *The Child*

Social Network Questionnaire (Chapter 1). *The Child Social Network Questionnaire* consisted of two parts: an interview about children's typical week of activities and demographic forms for each person in the child's social network.

Racial Preference Task

Children participated in a paradigm adapted from Shutts and colleagues (2011) to assess their racial preferences. Children participated in the task at a table outside of an exhibit designed for infants to 10-year-olds. On an iPad, children were introduced to two different-race children side-by-side. The faces of the children were from the CAFÉ dataset on Databrary (LoBue, 2014; LoBue & Thrasher, 2015). Each trial had one White child paired with either an Asian child, Black child, or Hispanic child. There were five trials for each pair type for a total of 15 trials. For each trial, children were introduced to each child and told an identical description about the child. For example, the experimenter would say, "This is Grace. She likes to go to the zoo. This is Zoe. She likes to go the zoo. Who would you like to be friends with?" (See Supplemental Materials for the names and descriptions that were used). Children were then instructed to point to who they would like to be friends with. The stimuli were gender-matched to the participant and the 15 trials were shown in a randomized order. There were two different sets of stimuli to counterbalance the side the faces were presented. While children completed the Racial Preference Task, their parents participated in *The Child Social Network Questionnaire*.

The Child Social Network Questionnaire

The Child Social Network Questionnaire is a method to capture young children's social networks (Chapter 1). The questionnaire is designed to assess infants' and children's social networks. Young children's social networks are the people that the child interacts with on a regular basis – a child's social network captures both the number of people they interact with on a regular basis (Network Size) and attributes of the people, which make-up the diversity of the social network (race, languages they speak, gender, etc.). *The Child Social Network Questionnaire* is administered in two parts: 1) a parent interview to collect information about children's typical week of activities and 2) a form to collect demographic information for each person the child sees on a regular basis. For the parent interview, parents were asked to describe their child's "typical week" of activities. The experimenter would ask, "Now I want you to think about [CHILD'S] schedule Monday through Friday – what does that look like for [HER/HIM] and what kinds of activities are they doing?". The experimenter would prompt the parent to describe their child's typical week of activities and the experimenter would record the people that the child saw on a regular basis (See Appendix A for the interview script). The goal of the parent interview is to generate a list of people the child interacts with on a regular basis. Parents' description of their child's typical schedule served as a memory prompt and allowed the experimenter to make sure all the individuals a child knows is accounted for. After parents described their child's schedule for Monday-Sunday, the experimenter asked "Is there anyone else that you think is worth mentioning that your child sees on a regular basis?"

After the initial interview, parents were asked to fill out a demographic form for each of the people in their child's social network. The demographic form asked about each individual's age, gender, race, languages they spoke, and different contexts that they interacted with the child (see Appendix C).

Social Network Measures

The Child Social Network Questionnaire extracts several different network properties that map onto dimensions of children's early social experience. The analysis was focused to the following variables, which we describe below: Network Size, Network Racial Diversity (as assessed by Racial Entropy and Racial EI Index), and Network Structure (as assessed by Proportion Zero Entropy Components and Network Structure Classification). See Chapter 1 for more details on children's social network properties.

Network Size. Network Size is the total number of people (also called 'nodes') the child sees on a regular basis. This number was determined from the interview. Most nodes in children's social networks are individual people; however, there are some "group level" nodes for this dataset. In the network science literature, there is no right answer to what the boundaries of the network should be – the research question determines the network space (Borgatti & Halgin, 2011). The research question dictates that the network space should be who the child "knows" and has regular contact. A parent had to report that the child knew the person as an individual for that person to be their own node. For example, if the parent reported that the child was in daycare or preschool, the experimenter would ask "Are there any kids in the class that stand out as friends?". In addition to the individual friend nodes there would also be a node for "daycare/preschool class" which is a node that includes multiple people.

Network Racial Diversity. There are two conceptually distinct measures to quantify network diversity – entropy and EI Index. Entropy describes the representation of different social groups in the network and the EI Index indicates how diverse the network was relative to the child. Racial Entropy and Racial EI Index were calculated for each child using the egor package in R (Krenz et al., 2020).

Racial Entropy. For network science, entropy indicates the relative presence of different social categories among the nodes in a network and is calculated as follows for a given probability vector of P(X): $H(X) = - \sum P(X) * log2(P(X))$ (Drost, 2018; Krenz et al., 2020; Shannon, 1948). A score of 0 indicates that there is no diversity of categories; all the nodes share the same attribute, which in this case means all the nodes are the same race. A higher entropy scores indicates a greater representation of different racial categories. See Figure 45 for example networks and corresponding Racial Entropy scores.

In order to calculate racial entropy, each alter needed to be classified by a discrete racial category. The racial categories that were used to calculate entropy were the following: African or Black-American, Asian or Asian-American, European or White-American, Hispanic or Latino-American, Native American, Mixed/Biracial, or Other. For the Mixed/Biracial category, parents could indicate that the node was biracial by selecting "Mixed/Biracial" or by selecting more than one race. For some nodes, there was detailed information (for example, if the alter was a Black/White biracial or Asian/White biracial), but for some alters the only data available is that the individual is biracial. As such, all biracial alters were categorized as "Mixed/Biracial". This is imperfect as biracial individuals are not a monolith; however, this method of categorization retained all the racial information about the alters.

Racial EI Index. The second measure of Network Racial Diversity is the Racial EI Index. The EI Index is a measure of homophily the child shares with the network and is calculated as follows: *(Number of Different Nodes – Number of Same Nodes)/Network Size* (Krackhardt & Stern, 1988; Krenz et al., 2020). The EI Index ranges from -1 to 1; a score of -1 indicates the entire network is the same as the child on some attribute and a score of 1 would indicate that the entire network is different from the child on some attribute (e.g., if a White child had a network where all the nodes were White, they would get a score of -1; the same is true if a Black child had a network where all the nodes were Black).

To calculate the Racial EI Index, each node had to be classified as either same-race or different-race compared to the child. For monoracial children, this was simple – any node that was not the same-race as the child was coded as different-race (i.e., for a White child, any alter that was not also White was coded as different-race). For biracial children (n = 27), the alter was classified as same if they were either races of the child. For example, for a Black/White biracial child any node that was White or Black would be coded as same-race. All other alters would be coded as different. For our biracial children, parents either provided detailed information for their child or it was possible to deduce the races of the child by looking at the races the parents reported for themselves; for three subjects, there was not enough detailed information and therefore could not calculate a Racial EI Index score for them.

Network Structure. There were two ways to describe Network Structure to capture how racial diversity was structured in the social network – Proportion of Zero Entropy Components and Network Structure Classification.

Proportion of Zero Entropy Components. In addition to calculating the overall Racial Entropy for the social network, it was also possible to calculate the Racial Entropy of each *component* in the child's social network (Table 4). On average, children had 2.9 components (*SD* = 1.1, range: 1-7; Table 9). The Racial Entropy was calculated for each component and a Proportion Zero Entropy Component score was computed for each child; this was the proportion of components in the social network that had zero Racial Entropy. Phrased another way, this was the proportion of components that had no diversity of racial groups represented in the component. A proportion greater than 0.50 would mean that more than half the components in the social network had no racial diversity. A proportion of 0 would indicate that all the components in the social network had some level of racial diversity – each component had members of different racial groups represented (Figure 7).

Network Structure Classification. Using the Proportion of Zero Entropy Components, children were classified as either having Integrated Networks, Segregated Networks, or No Diversity Networks. Children that had all components with zero Racial Entropy were No Diversity Networks (n_{White} = 2, $n_{Racialminority}$ = 4). Children where 50% or more of their components had zero Racial Entropy were Segregated Networks (n_{White} = 21, $n_{Racialminority}$ = 14) and children where less than 50% of their components had zero Racial Entropy were Integrated Networks (n_{White} = 25, $n_{Racialminority}$ = 32). A chi-square test of independence was performed to see if the network types varied by our racial subgroups and the test was not significant ($X^2(1, N = 98) = 2.89$, $p = .24$). There was no evidence that the network structures differed by the child's race.

Neighborhood Racial Diversity

In addition to *The Child Social Network Questionnaire*, the zip-code of where participants lived was collected to be able to calculate the neighborhood racial diversity from the US American Community Survey from the US Census. The Neighborhood Racial Entropy was calculated for each subject (Hwang, 2018).

Results

Racial Preference Task Performance

Each child had a proportion of trials where they chose the White stimulus and a proportion of trials where they chose the Nonwhite stimulus (Figure 44). Paired sample t-tests confirm that for both White subjects and Racial minority subjects, children chose the White stimulus more than the Nonwhite stimulus (White children: M_{White} = .64(.20), $M_{Nonwhite}$ = .36(.20), $t(50) = 4.64$, $p < .001$; Racial minority: M_{White} = .58(.21), $M_{Nonwhite}$ = .42(.21), $t(49) = 2.71$, $p < .01$). This finding is consistent with prior work for this age group (see Hailey & Olson, 2013 for a review). See Supplemental Materials for a breakdown of how each racial subgroup performed on this task.

Before presenting preregistered analysis, Table 9 shows descriptive statistics for the social network variables of interest: Network Size, Racial Entropy, Racial EI Index, and Network Structure Measures, Per the pre-registered analysis, the data was analyzed separately by child race.

Social Network Variables

Table 9 shows descriptive information for the Social Network Variables – for the entire sample and divided by our racial subgroups. On average, children had a Network Size of 14 people (SD = 4.5 people, range: 6 - 26 people). Figure 45 and Figure 46 show the histograms of Network Racial Entropy and Network Racial EI Index, respectively. The pre-registered analysis indicated that both measures of Network Racial Diversity would be explored; however, the Racial EI Index for this particular sample is right-skewed (Figure 46). The only transformation that can be performed on this variable is a cubed root transformation because this measure has negative values, but the transformation does not fix the skew of the distribution and violates the assumption of normality. Therefore, the Racial EI Index was dropped from analysis.

Table 10 shows the correlations between the Social Network Variables. This study wanted to explore how Network Racial Diversity interacts with both Network Size and Network Structure to relate to children's racial friendship choices. To accomplish this aim, the first analysis that was conducted was a fully interactive model of Network Racial Entropy and Network Size. For Racial minority subjects only, Network Racial Entropy and Network Size were weakly correlated (*rho* = .31, $p < .05$; Table 10); therefore, the tolerance was calculated for each variable. Tolerance is a measure that indicates how much the variables of interest can vary independently from each other and ranges from 0 – 1. In a model with X and Y predictors, a tolerance of .55 would mean that when you hold variable X constant, variable Y can vary independently by 55%. The model would be acceptable if it had a tolerance at .75 or above. This would mean that our correlated variables can vary 75% independently from each other. The second analysis used the Proportion of Zero Entropy Components and the Network Structure Classification to explore how the structure of racial diversity related to children's pro-White bias. Finally, Network and Neighborhood Racial Diversity were interacted to explore whether and how both proximal and distal social properties related to children's racial friendship choices.

Pre-Registered Analysis

In the pre-registered analysis, logistic mixed-effects models were conducted using children's binary responses on the task as the DV for a total of 15 trials (1: choose White, 0: choose non-White). It was pre-registered to conduct single term regressions for Network Size and Network Racial Entropy as well as the fully interactive model. The fully interactive model is reported below. The single term regressions show the same pattern of results as the fully interactive model and can be found in the Supplemental Materials.

Network Racial Entropy x Network Size Model

A logistic mixed-effect model was conducted and included Racial Entropy, Network Size, and the interaction between Racial Entropy and Network size as fixed effects and Subjects as a random effect. For White subjects, the model revealed null results. There was no significant main effect for Racial Entropy (β = .32, p = .85), Network Size (β = .53, p = .26), and the interaction was not significant (β = -.05, p = .91). It is possible the model was underpowered, which is why it revealed a null result. To explore this null model, the main effect model was run only testing for the effects of Network Size and Racial Entropy. The main effect model revealed a significant main effect of Network Size ($\beta = .49$, $p = .02$) and no significant effect of Racial Entropy ($\beta = .14$, $p = .63$). Even controlling for Network Racial Entropy, there was still an effect of Network Size; White children in larger networks exhibited more pro-White bias (Figure 47).

The identical interactive model was conducted for the Racial minority subjects. There was no significant main effect of Network Size ($\beta = .83$, $p = .17$) or Racial Entropy ($\beta = 2.15$, $p = .12$), but the interaction was marginally significant ($\beta = -.71$, $p = .07$; Figure 48). There was weak evidence that children in large networks with high amounts of Racial Entropy exhibited the least amount of pro-White bias. Similar to the White subjects, the main effect model was also conducted and that analysis revealed a null result. The main effect model did not show significant main effects for either Network Size ($\beta = -.15$, $p = .56$) or Racial Entropy ($\beta = -.34$, $p = .18$). As stated above, Network Size and Racial Entropy were correlated for the Racial minority subjects. The tolerance was calculated for the interactive model and got a tolerance of 0.85 for each of our variables; this means that Network Size and Racial Entropy could vary 85% independently for each other.

Summary of Network Racial Entropy x Network Size Model

There was no evidence that Network Racial Entropy was related to White children's pro-White bias. Interestingly, Network Size did relate to their pro-White bias, but in the opposite, predicted pattern. White children in larger social networks exhibited more pro-White bias. For the Racial minority subjects, there was weak evidence to suggest that Network Racial Entropy affects children's racial friendship choices depending on the size of the social network. For Racial minority children in networks with low amounts of Network Racial Entropy, their pro-White bias increased with Network Size. The opposite pattern was observed for children with high amounts of Network Racial Entropy – as Network Size increased, the amount of pro-White bias decreased. There is evidence to suggest that the representation of different racial groups does not have the same impact across children – the size of the network in which children experience diversity seems to relate to their racial friendship choices.

Network Structure Analysis

The next set of analyses were pre-registered exploratory analyses. These analyses explored how network structure interacted with racial diversity to relate to children's pro-White bias. While there are hints from prior literature about how racial diversity might impact children's racial bias (e.g., Deeb et al., 2011; Rutland et al., 2005), there is no prior work that has explored how the structure of children's relationships relates to their intergroup cognition. For example, does it matter if the racial exposure in their network is dispersed or more connected? The analyses presented below start to answer this question.

Proportion of Zero Entropy Components

Social networks provide a novel method to ask how the Racial Entropy of each *component* in the child's social network might relate to their racial friendship choices. Specifically, how does the Proportion of Zero Entropy Components relate to children's friendship choices? The average Proportion of Zero Entropy Components for White children was 0.36 (SD = 0.26) and the average for Racial minority children was 0.26 (SD = 0.33). The Proportion of Zero Entropy Components was analyzed to see if it was related to children's pro-White bias.

A logistic mixed-effect model was conducted using the Proportion of Zero Entropy Components as a fixed effect. For White children, there was a significant negative effect of Proportion Zero Entropy Components (β = -1.64, p = .002; Figure 49). The higher the Proportion of Zero Entropy Components in the network, the less pro-White bias children exhibited. Phrased another way, White children that had more integrated networks, or networks where more than half of their components had some racial diversity, showed higher rates of pro-White bias.

The identical analysis was conducted with the Racial minority children and the model revealed a null result; there was no evidence that the Proportion of Zero Entropy Components was related to Racial minority children's pro-White bias ($\beta = -.31$, $p = .46$; Figure 49).

Network Structure Classification

The next analysis used the Network Structure Classification to see if there was a difference in task performance based on the structure of the social network. Given the small number of subjects that had No Diversity networks ($n = 6$), these subjects were excluded from the following analysis. Using the proportion of trials children chose the White stimulus as the DV, two-sample t-tests were performed to see whether there was a difference for children with Integrated versus Segregated Networks. For White children only, there was a significant difference between the Network Structure types. Consistent with the previous analysis, children with Integrated Networks showed more pro-White bias than children with Segregated Networks ($M_{Integrated} = .70(.21)$, $M_{Segregated} = .60(.14)$; $t(42) = 2.2$, $p = .03$; Figure 50). There was no evidence that Racial minority children performed differentially on this task based on the structure of their social network ($M_{Integrated} = .54(.18)$, $M_{Segregated} = .62(.24)$; $t(28) = -1.5$, $p = .14$; Figure 50).

Summary of Racial Diversity and Structure Findings

For White subjects, our results showed Network Racial Diversity impacted children's pro-White bias differently for children in different structured networks. A greater Proportion of Zero Entropy Components was related to less pro-White bias. White children in more integrated, as opposed to more segregated networks, exhibited the most pro-White bias. This analysis has demonstrated that not all exposure to racial outgroups is created equal; how that diversity is distributed in the network seems to relate to children's emerging racial attitudes.

Network and Neighborhood Racial Diversity

Finally, we tested whether the diversity of the close, personal relationships interacted with the diversity of the neighborhood to impact children's pro-White bias. A logistic-mixed effect model was conducted to test the effects of Network and Neighborhood Racial Diversity on children's pro-White bias. For White subjects, there was no significant effect of Neighborhood Racial Diversity ($\beta = 1.06$, $p = .14$), but a significant effect of Network Racial Entropy ($\beta = 1.72$, $p = .04$) and the interaction was significant ($\beta = -1.41$, $p = .05$; Figure 51). Interestingly, there was a main effect such that White children in more racially diverse networks exhibited more pro-White bias; however, the interaction demonstrates that this effect was weakened for children in highly diverse neighborhoods. White children with both high network and neighborhood racial entropy exhibited the least amount of pro-White bias. For Racial Minority subjects, the model revealed null results. There was no effect of Neighborhood Racial Entropy ($\beta = 1.01$, $p = .41$), Network Racial Entropy ($\beta = .48$, $p = .68$), and the interaction was not significant ($\beta = -.66$, $p = .44$; Figure 51).

Discussion

This study provided evidence that Network Racial Diversity was related to children's racial friendship choices, but it depended on the structure of the social network and children's broader social environment. Across both racial groups, Network Racial Diversity related to children's racial bias differently depending on the network structure. For Racial minority children, there was weak evidence that the Network Racial Diversity related to their racial friendship choices, but it depended on the size of the social network; Racial minority children with high amounts of Network Racial Diversity in large networks exhibited the least amount of pro-White bias. For White children, Network Racial Diversity related to their pro-White bias depending on the structure of their social network and how that social network was situated in the broader social environment. In an analysis that looked at the racial diversity of both close, personal contact and the broader neighborhood, White children with high amounts of racial diversity in both environments exhibited the least amount of pro-White bias. Surprisingly, there was also evidence to suggest that White children in Integrated Networks and White children in large social networks exhibited the most pro-White bias.

These findings demonstrate that the structure of children's social worlds was related to their racial friendship choices. This suggests that from an early age children are sensitive to the structure of their social world; the ways in which racial outgroups members are clustered in the social network provide information to children about the nature of these socially constructed categories. This study builds on prior work to ask about how contact with racial outgroup members affects racial friendship choices; however, this study is the first of its kind to ask about whether the structure and pattern of this racial diversity was related to children's racial bias.

Interestingly, White children with Integrated Networks exhibited greater racial bias than White children in Segregated Networks as did White children in larger social networks. Although this is conceptually consistent with prior work that has shown that White Americans find increased racial diversity in their neighborhoods threating, Intergroup Contact Theory would have made the opposite prediction as would have the predictions from a social network perspective. As shown in Chapter 1, as Network Size increases other aspects of the network change as well – the racial diversity increases, the number of components increases, and the proportion of adults and kin decreases. This suggests that as Network Size increases, children's opportunity to interact with outgroup members and people they are not as familiar with also increases, which might have led to less pro-White bias. The positive effect of Network Size on White children's pro-White bias raises the possibility that the quality or nature of these relationships might matter for racial bias. It is possible it is not just the quality of the relationships between the alters and child that might matter, but it also might be the quality of relationships between the alters themselves that matter.

Children in large networks not only interact with more people than children in small networks, but they also regularly watch other people in their network interact with each other. The positive effect of Network Size raises the possibility that children's weak ties interact in such a way to reinforce White children's ingroup preference. A limitation of ego-centric network research is that it is difficult to have parents provide subjective ratings about a relationship between two other people because it introduces measurement error (Blair et al., 2004; Epley, 2008; Perry et al., 2018); however, future research could more closely examine the alter-alter interactions to explore whether and how those relationships relate to children's racial bias.

The findings also highlight that Network and Neighborhood demographics might provide different dimensions of diversity in early childhood. For this particular sample, there was no evidence that Network and Neighborhood racial diversity were correlated (Table 10); however, for White children there was an interaction such that children with both high Network Racial Diversity and high Neighborhood Diversity exhibited the least amount of pro-White bias. This suggests that children are not only sensitive to their immediate social world, but also the broader community in which their network resides. This also suggests that the ways social network properties might relate to social cognitive development could vary based on the broader social context in which the social network is embedded. As demonstrated with the results here, high amounts of Network Racial Diversity related to children's racial bias differently depending on the demographics of the broader community. Future work exploring how exposure to racial outgroup members impacts intergroup cognition should take this into consideration. This study highlights that neighborhood demographics do not necessarily map onto the characteristics of the close, personal relationships and that these different dimensions of diversity might contribute to children's social cognitive development in distinct ways.

One limitation of the current study is the small number of participants in each of the racial subgroups for the Racial minority subjects. As stated above, any analysis that would have included child race as a factor would have been underpowered, so it is difficult to draw any strong conclusions from our Racial minority sample. Nevertheless, this study does suggest that there are differences in the structure of the social world for racial majority and racial minority children; while there were no correlations between Network Size and Network Racial Diversity for White children, there were positive correlations for the Racial minority subjects (Table 10). Evidence from this study, in combination with the results reported in Chapter 1, raise the possibility that the ways diversity and out-group exposure are manifested in the social network differ across racial groups. This further raises the possibility the ways that diversity and out-group exposure affect cognition might vary for racial majority and racial minority children. Larger sample sizes of a racially diverse sample in future work can start to address this possibility.

An interesting and unexpected aspect of this data is the high number of biracial subjects that make up the Racial minority group, particularly the high number of White/Black and White/Asian biracials (Total biracials: n = 27; White/Black biracials: n = 5; White/Asian biracials: n = 17). Current social identity theories do not account for the fact that biracial individuals have more than one in-group and that their identity may fluctuate over time and across different social contents (Gaither, 2015). For example, prior work with biracial children has shown that when White/Black and White/Asian biracials are primed with their White identity, they are more likely to choose their White in-group in a social affiliation task similar to the task used in the present study (Gaither et al., 2014). Although children were not formally primed in this study, the nature of task design might have unintentionally primed biracial children's White identity because they were always shown a White child to choose from. Future work exploring how racial diversity relates to biracial children's racial friendship choices should employ a method that does not unintentionally prime identity.

In summary, this study harnessed the power of social network analysis to describe the structure of children's social worlds in relation to their intergroup cognition – it is the first study of its kind to capture and describe the structure of children's regular social contact. These findings suggest that from an early age children are sensitive to how racial outgroup exposure is patterned in their social network and also their broader community. For White children in particular, racial diversity exposure was not created equal – the structure of the racial diversity and how it is embedded in the broader social environment was related to their racial bias. As previously stated, children's contact with different racial groups is likely not the sole predictor of racial bias in childhood; however, this study provides important insight to the ways in which early social environments relate to emerging racial bias.

Table 9

Descriptive Social Network Variables

	Total Sample	White subjects	Racial minority subjects
	M (SD)	*M (SD)*	*M (SD)*
Network Size	14 (4.5) people	14.6 (4.8) people	13.4 (4.2) people
Network Racial Diversity			
Racial Entropy	1.16 (0.54)	1.03 (0.47)	1.29 (0.59)
Racial EI Index	-0.47 (0.39)	-0.45 (0.33)	-0.49 (0.45)
Network Structure			
Number of Components	2.9 (1.1)	3.1 (1.1)	2.8 (1.2)
Component Ratio	0.15 (0.1)	0.16 (0.1)	0.14 (0.1)
Density	0.56 (0.21)	0.56 (0.23)	0.57 (0.2)
Friends			
Number of Friends	2.7 (1.8) friends	3.1 (2.0) friends	2.4 (1.5) friends
Friendship Racial Entropy	0.48 (0.58)	0.46 (0.61)	0.50 (0.55)
Friendship Racial EI Index	-0.40 (0.74)	-0.56 (0.59)	-0.20 (0.87)

Note. After correcting for multiple comparisons, there was no evidence White subjects and Racial minority subjects differed on these social network variables.

Table 10

Correlations of Network Variables

	White subjects	Racial minority subjects
	Spearman rho	*Spearman rho*
Network Size x Network Racial Entropy	-.06	**.31***
Network Size x Network Racial EI Index	-.10	**.39****
Network Size x Prop. Zero Entropy Components	**-.37***	**-.40****
Network Racial Entropy x Network Racial EI Index	**.95*****	**.49****
Network Racial Entropy x Prop. Zero Entropy Components	**-.46****	**-.63*****
Network Racial EI Index x Prop. Zero Entropy Components	**-.43****	-.10
Network Racial Entropy x Neighborhood Racial Entropy	.28	.14

* p < .05 ** p < .01 *** p < .001

Note. The correlations reported are FDR corrected spearman correlations.

Figure 44

Racial Preference Task Performance

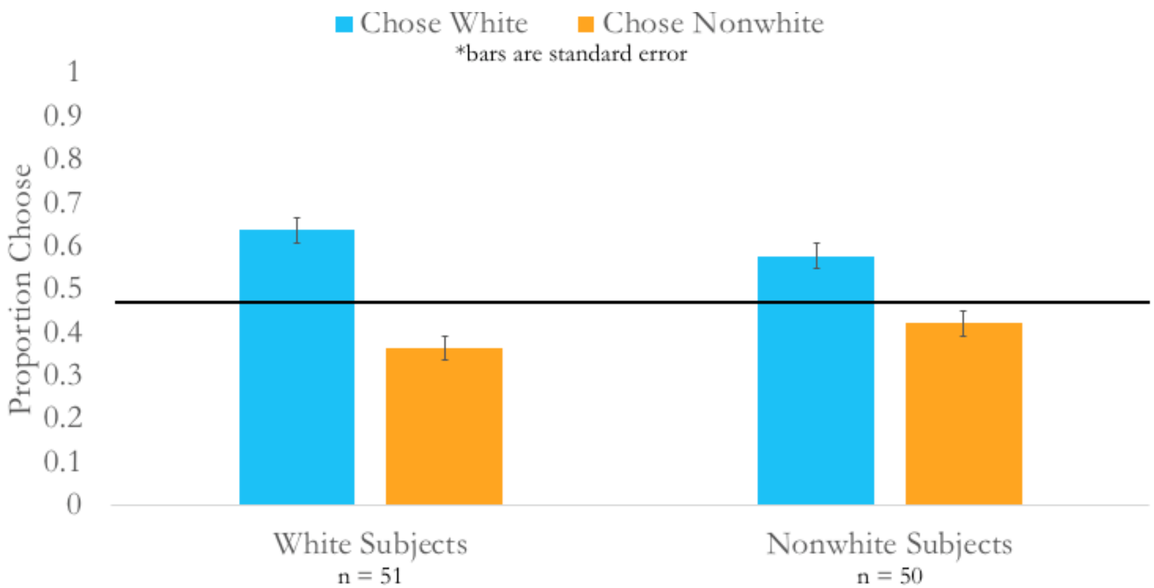
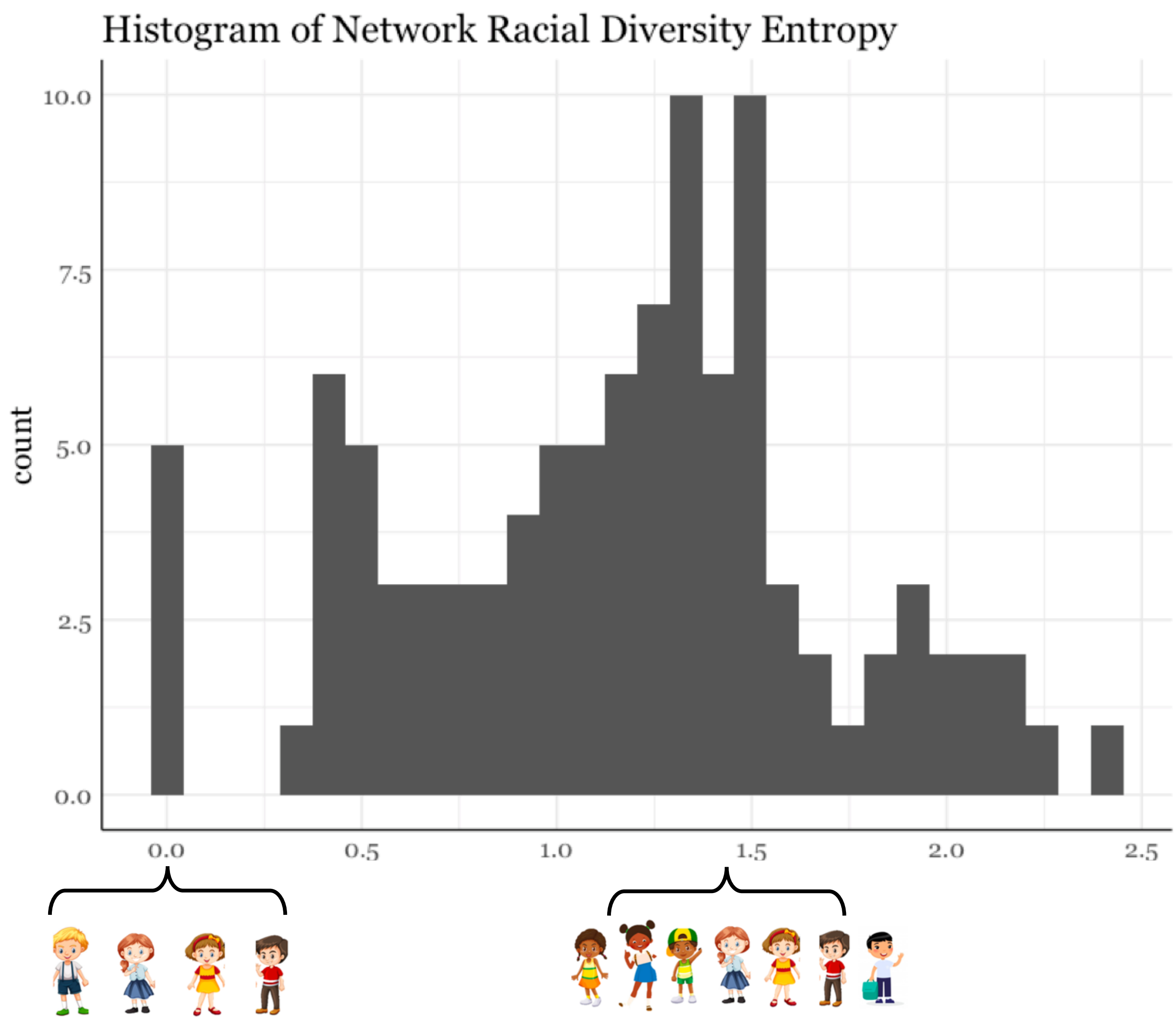


Figure 45

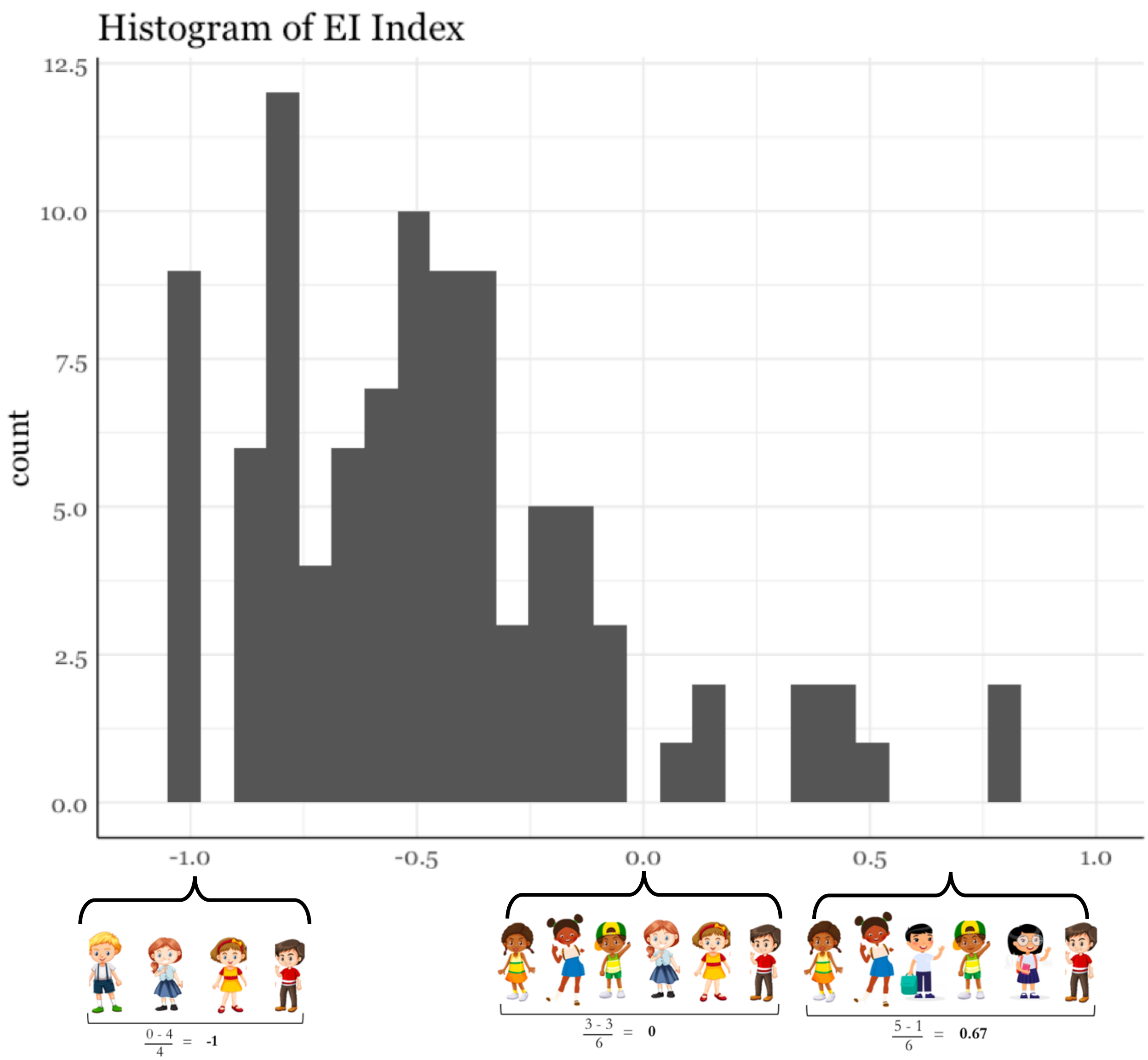
Histogram of Network Racial Entropy



Note. A value of 0 entropy means all the alters are the same race. In the sample network above, all the alters are White. The higher the value, the greater representation of different racial group members in the social network.

Figure 46

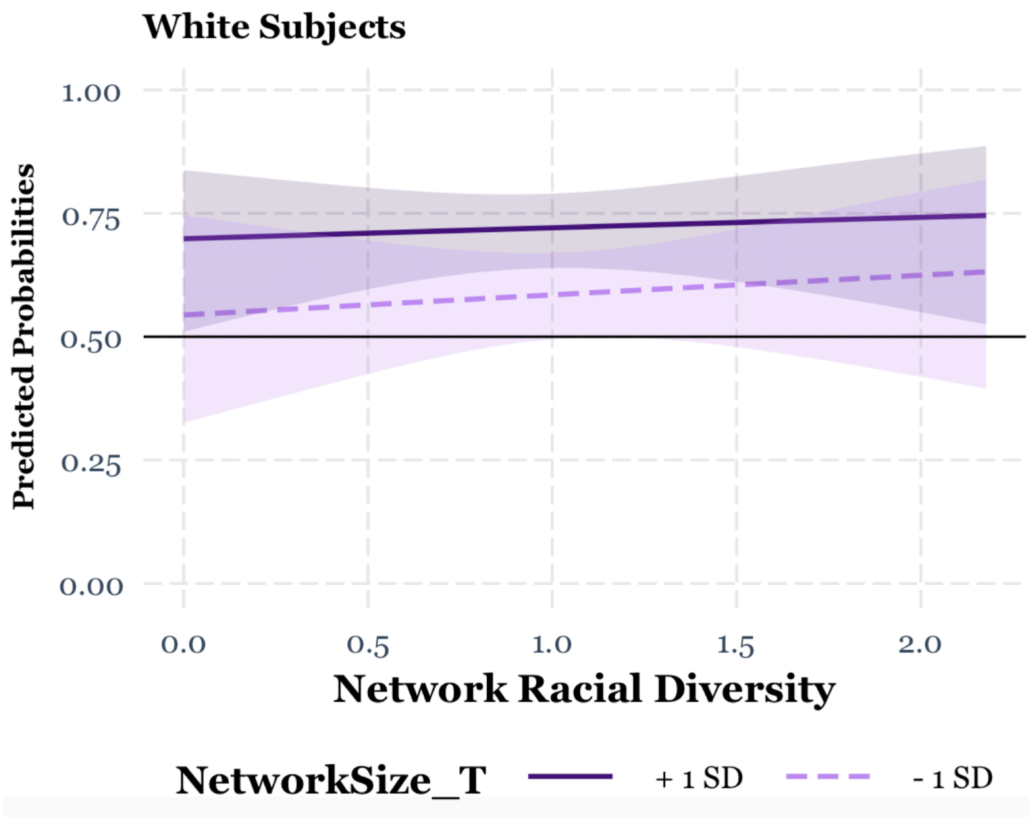
Histogram of Network Racial EI Index



Note. The above figure shows examples of the Racial EI Index for a White child. A network that is also all White would get a score of -1. A network where the majority of alters are not White would get a score greater than 0.

Figure 47

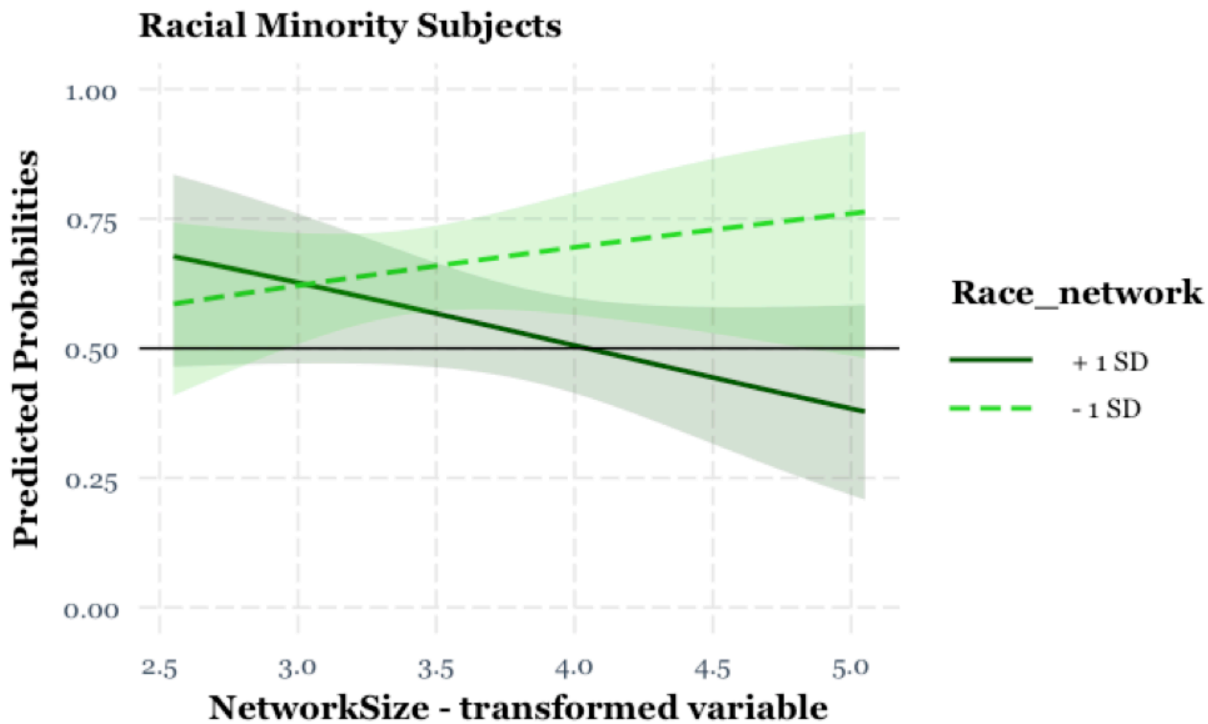
Network Size and Racial Entropy Model for White subjects



Note. Above 0.50 on the y-axis indicates more pro-White bias. The full interactive model revealed null results for Network Size, Racial Entropy, and the interaction. The main effect model revealed a significant main effect for Network Size (β = .49, p = .02), but not for Racial Entropy (β = .14, p = .63).

Figure 48

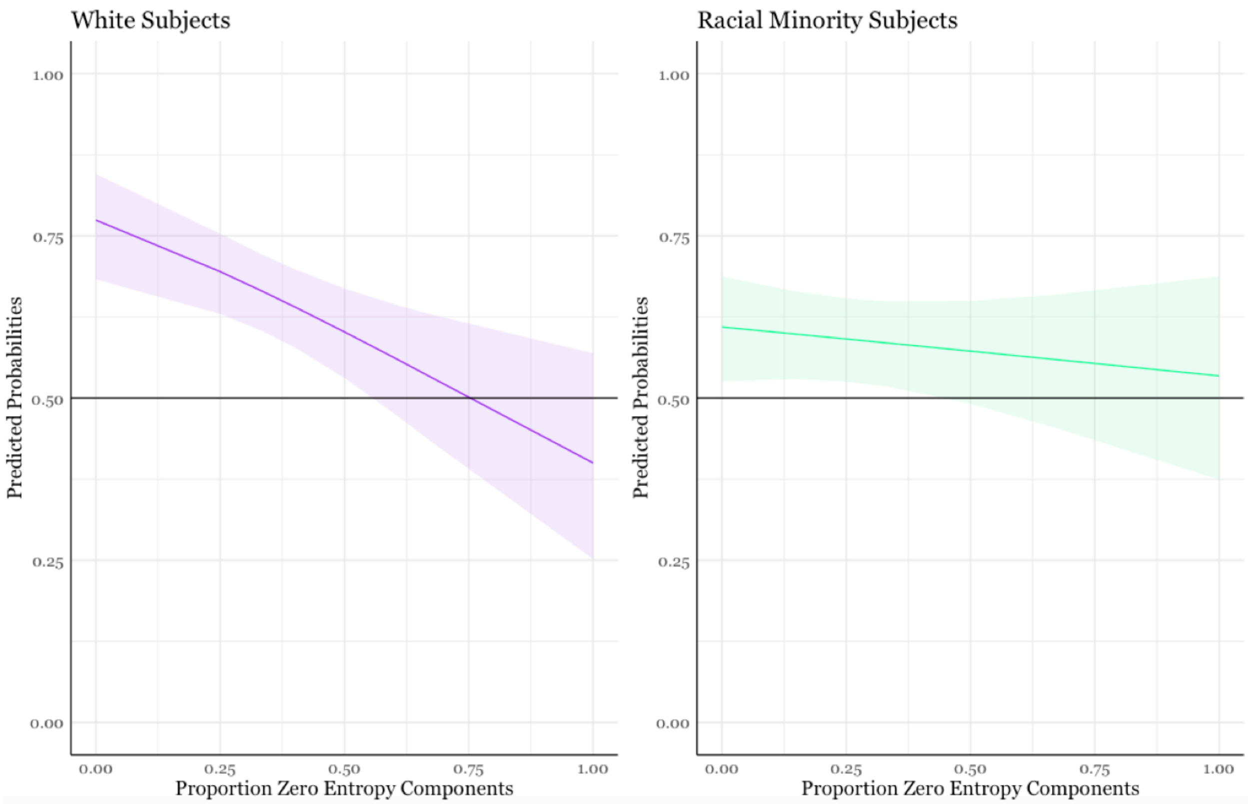
Network Size and Racial Entropy Model for Racial Minority subjects



Note. Above 0.50 on the y-axis indicates more pro-White bias. The model did not reveal significant main effects for either Network Size (*ß* = .83, *p* = .17) or Racial Entropy (*ß* = 2.15, *p* = .12). The interaction is marginally significant (*ß* = -.71, *ß* = .07).

Figure 49

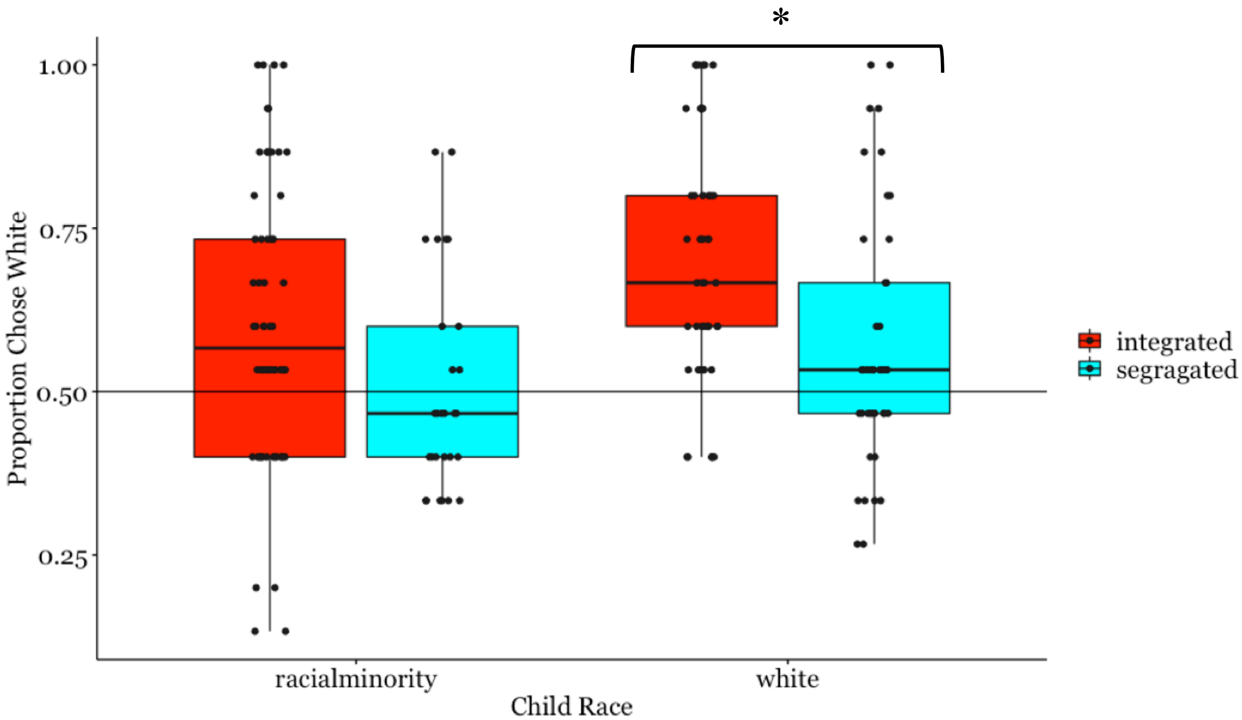
Proportion of Zero Entropy Components and Pro-White Bias



Note. Above 0.50 on the y-axis indicates more pro-White bias. For White subjects only, there was a significant, negative main effect of Proportion of Zero Entropy Components.

Figure 50

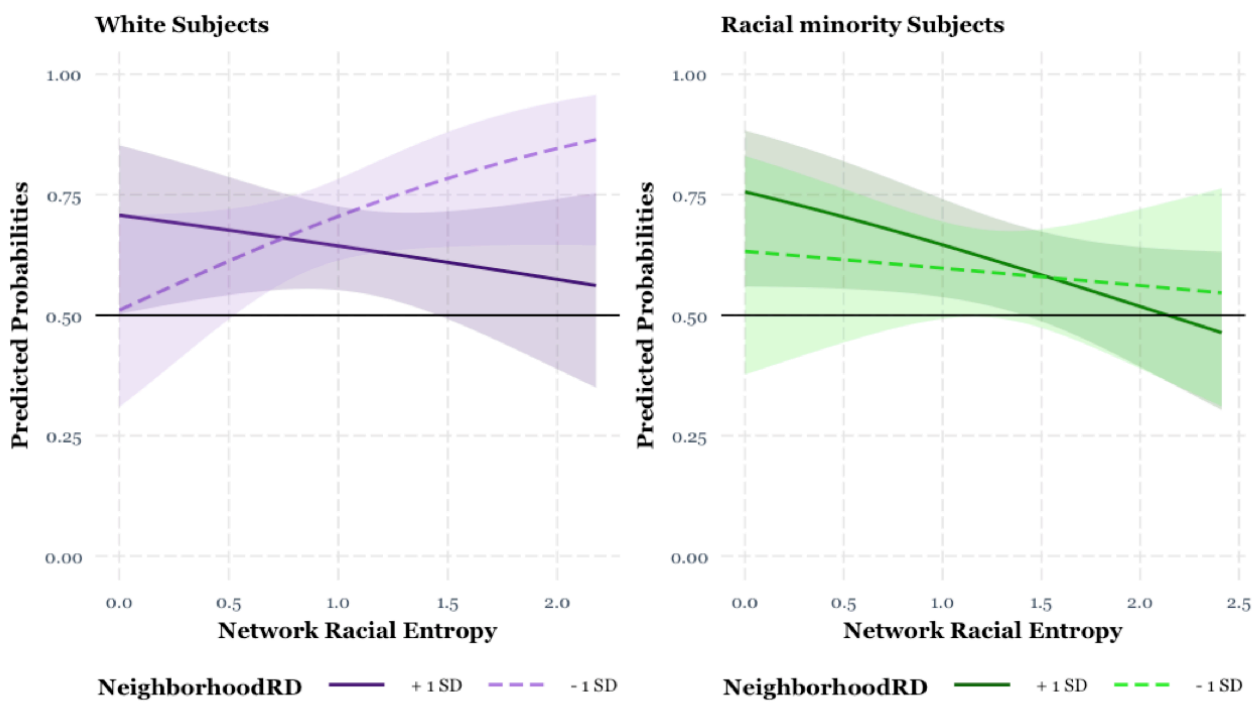
Network Structure Classification and Pro-White Bias



Note. For White children only, children in Integrated networks exhibited more pro-White bias than children in segregated networks ($M_{Integrated}$ = .70(.21), $M_{Segregated}$ = .60(.14); $t(42) = 2.2$, p = .03).

Figure 51

Network and Neighborhood Racial Entropy on Pro-White Bias

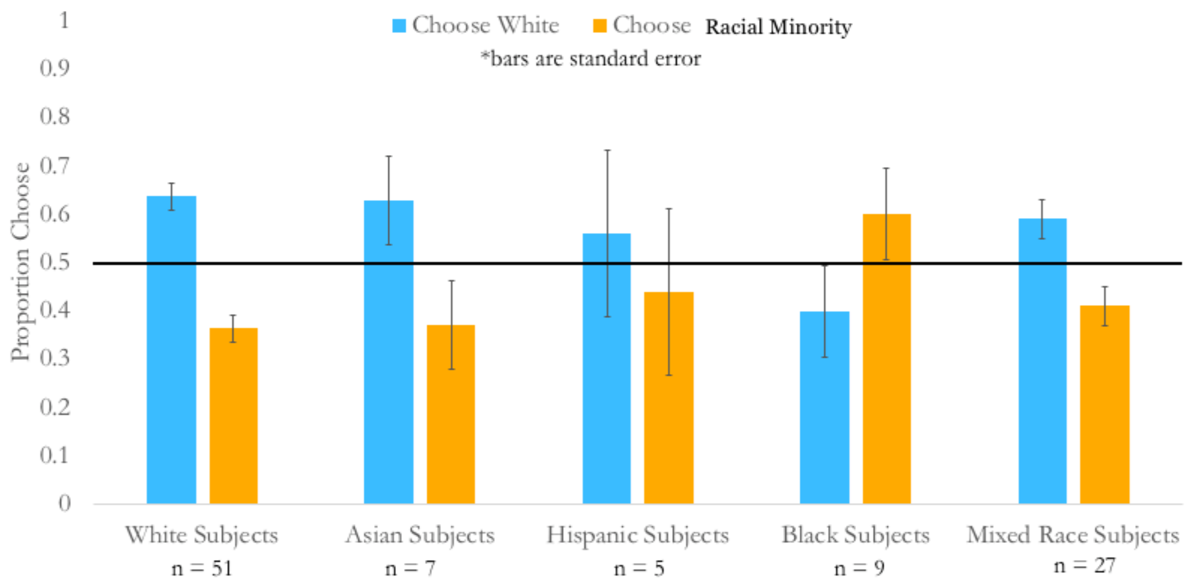


Note. Above 0.50 on the y-axis indicates more pro-White bias. For White subjects, there was no significant effect of Neighborhood Racial Diversity ($\beta = 1.06$, $p = .14$), but a significant effect of Network Racial Entropy ($\beta = 1.72$, $p = .04$) and the interaction was significant ($\beta = -1.41$, $p = .05$).`

Chapter 3 Supplemental Materials

Racial Preference Task Performance

Given the small number of participants for each of our racial subgroups we did not perform a formal analysis, but we provide the figure below for descriptive information.



Pre-registered Main Effect Models

Racial Entropy Main Effect Model

First testing our White subjects, we ran a logistic mixed-effect model including Network Racial Entropy as a fixed effect predictor and Subjects as a random effect and our analysis revealed a null result; there was no evidence that Racial Entropy is related to pro-White bias for White subjects (β = .08, p = .80). We ran an additional model and controlled for age and while there was still no evidence that Racial Entropy relates to White children's pro-White bias (β = .10, p = .72) there was a small, marginally significant effect of child age (β = .04, p = .06). Consistent with prior developmental work in this age range, as White children get older they start to exhibit more pro-White bias.

We ran the identical analysis for the Racial minority subjects and found a marginally significant effect of Racial Entropy on task performance – there is weak evidence that children with more Racial Entropy were less likely to exhibit a pro-White bias ($\beta = -.39$, $p = .086$).

Network Size Main Effect Model

The next set of pre-registered analysis looked to see how Network Size related to children's pro-White bias. For both groups of subjects, we conducted a logistic mixed-effect model including Subjects as a random effect, Network Size as a fixed effect, and the performance on the task as the DV. Network Size was square-root + .5 transformed because it is a small count variable (Kirk, 2013). For the White subjects, there was a significant main effect of Network Size ($\beta = .48$, $p = .02$). White children in larger social networks exhibited more pro-White bias. For racial minority subjects, our analysis revealed a null result; there was no evidence that Network Size related to racial minority subjects pro-White bias ($\beta = -.30$, $p = .23$).

Contrary to our prediction, White subjects in larger social networks exhibited more pro-White bias. There was no evidence that Network Size was related to Racial minority subjects' pro-White bias. Although the effect is small, Network Size and child age were correlated in this sample ($r = 0.25$, $p = 0.01$). To explore whether the Network Size effect is masking an effect for age for the White subjects, we ran a logistic mixed-effect model interactive model that included both child age and Network Size. The model failed to converge. We next ran the model just testing for the main effects of Network Size and child age and found a marginal effect for Network Size (ß = .39, $p = .08$) and no effect for child age ($\beta = 0.02$, $p = 0.23$). There was weak evidence to suggest that after controlling for child age, White children in larger social networks exhibited more pro-White bias.

Task Sentences

Below is a list of the descriptions children heard during the Racial Preference Task. The descriptions show the female names that were used. The male descriptions were identical, but used the following male names instead: Liam/Noah, William/James, Oliver/Benjamin, Elijah/Lucas, Owen/Wyatt, Mason/Logan, Alexander/Ethan, Jacob/Michael, Daniel/Henry, John/Jack, Jackson/Sebastian, Aiden/Matthew, Samuel/David, Joseph/Carter, Luke/Dylan.

White/Black trials:

1. This is Ava. She plays soccer. This is Olivia. She plays soccer. Who would you like to have as your friend?
2. This is Amelia. She is having a birthday party. This is Charlotte. She is having a birthday party. Who would you like to have as your friend?
3. This is Mia. She goes to school. This is Emma. She goes to school. Who would you like to have as your friend?
4. This is Isabella. She goes to the zoo. This is Sophia. She goes to the zoo. Who would you like to have as your friend?
5. This is Abigail. She reads books. This is Evelyn. She reads books. Who would you like to have as your friend?

White/Asian trials:

6. This is Harper. She eats pizza. This is Emily. She eats pizza. Who would you like to have as your friend?
7. This is Ella. She sings songs. This is Madison. She sings songs. Who would you like to have as your friend?
8. This is Grace. She eats chocolate. This is Chole. She eats chocolate. Who would you like to have as your friend?
9. This is Layla. She plays baseball. This is Nora. She plays baseball. Who would you like to have as your friend?
10. This is Zoey. She plays basketball with all her friends. This is Aubrey. She plays basketball with all her friends. Who would you like to have as your friend?

White/Hispanic trials:

11. This is Hannah. She goes to the park. This is Lily. She goes to the park. Who would you like to have as your friend?
12. This is Addison. She watches TV. This is Eleanor. She watches TV. Who would you like to have as your friend?
13. This is Natalie. She plays piano. This is Luna. She plays piano. Who would you like to have as your friend?

14. This is Violet. She has a pet cat. This is Claire. She has a pet cat. Who would you like to have as your friend?
15. This is Anna. She plays video games. This is Samantha. She plays video games. Who would you like to have as your friend?

General Discussion

This dissertation provides three meaningful contributions to the field of developmental psychology. First, this dissertation provides a method to capture young children's social networks. As I argued across 3 chapters, social networks are a novel, innovative way to capture and describe early social environments. Second, this dissertation provides a framework that developmental psychologists can use to generate questions about how variations in early social experience relate to social cognitive development. Finally, this dissertation provides data to empirically test the hypotheses that are generated from a social network perspective.

Summary of Findings

Chapter 1 presented the method I developed – *The Child Social Network Questionnaire*. This chapter introduced social network analysis, an approach developed in sociology, that I argued can be used to describe children's early social environments. This chapter showed that several aspects of children's early social experience can be described with network properties and I explored how those properties vary across developmental time, social group membership, and childcare experience.

Chapter 2 used *The Child Social Network Questionnaire* to explore how aspects of 3-year-olds' social networks related to their PT skill. Prior work with adults has suggested that social network size is positively related to perspective-taking ability (Stiller & Dunbar, 2007); the more people a person interacts with, the better they are at taking another person's perspective. Prior work with children has shown that children with multilingual exposure are better at perspective taking (Fan et al., 2015; Liberman et al., 2016). Results demonstrated that three-year-old children in larger social networks exhibited superior PT skill compared to children in smaller social networks, particularly when the partner did not share the child's view of the specific object. Exploratory analyses suggested that Network Linguistic Diversity also related to PT performance. Children in smaller social networks demonstrated better PT skills when their network was less linguistically diverse. These findings provide evidence that the size of and diversity in children's social networks is closely linked to their ability to take others' perspectives.

Chapter 3 used *The Child Social Network Questionnaire* to explore how social network diversity and structure related to 3- and 4-year-old's racial preferences. While there is an abundance of prior work that has documented the development of racial bias (see Hailey & Olson, 2013 for a review), very little work has explored how variation in out-group racial exposure affects this preference. This study explored whether Network Racial Diversity interacted with Network Size, Network Structure, and the broader social environment (Neighborhood Racial Diversity) to relate to children's racial friendship choices. Results showed across racial groups, Network Diversity has a different effect depending on Network Size and Structure. For Racial minority children, there was weak evidence Network Racial Diversity interacted with Network Size; children with high amounts of Network Racial Diversity in large social networks exhibited the least amount of pro-White bias. For White children, racial outgroup exposure was not created equal – children with high amounts of both Network and Neighborhood Racial Diversity exhibited the least amount of pro-White bias, as did children in Integrated versus Segregated Networks. There was also evidence that White children in larger social networks exhibited more pro-White bias. This raises the possibility that something about the interactions of weak ties in children's networks reinforces White children's early in-group preferences.

Taken together, these studies demonstrate how a social network perspective can be used to ask innovative, novel research questions in developmental science. Prior developmental research that has explored how variations in early social experience relate to social cognitive development has been narrow in scope; this work studied early social experience as isolated components of experience. My results illustrate the ways in which early social experience is complex and embedded and how social networks provide a powerful, flexible tool to explore this complexity in a unified framework.

Implications of a Network Perspective in Developmental Science

A social network perspective in developmental science illustrates the novel, innovative questions that can be asked about the structure of children's early social environments. The greatest strength of social networks is that it is a tool and framework that can contend with the dimensions of early social experience that covary. As demonstrated across 3 chapters, children's early social worlds are complex and embedded. For example, children who attended out-of-home childcare had higher levels of racial diversity in their network than children not in out-of-home childcare; children in larger networks also had networks that were more complex. While the greatest strength of a social network is its ability to describe complex social environments, it is also its greatest limitation in trying to understand how network properties affect social cognitive development.

Given that aspects of social experience covary, it becomes difficult in any network study to distinguish which specific properties relate to an outcome. A social network perspective often raises more questions than it answers; however, these questions are necessary to refine our theories on how early social environments relate to the developing child. For example, prior developmental work has shown that children undergo massive gains in their cognitive skills after they start to attend school (see Cici, 1991 for a review). The data presented in Chapter 1 show there were differences in the early social environments of children with and without out-of-home childcare – children with out-of-home childcare had more racially diverse networks and had more complexity in their network structure. This raises the question of whether the gains children experience in their cognitive skills is related to formal schooling experience or whether it is related to these other aspects of their proximal social environment. With sufficient enough data and statistical power, social networks can be used to explore this question – and ones similar to it – to further refine developmental theories about how early social environments relate to social cognitive development.

Another limitation of network science research is that it is correlational and it is impossible to determine the directionality of a given effect. Did the individual influence their social network or did the social network influence the individual? Network scientists take different approaches on this problem to generate their questions and hypotheses. For example, the social brain hypothesis takes the theoretical stance that it is individual differences in the organism that drives their eventual social environment (Barrett et al., 2003; Dunbar, 1998). Ultimately, both stances – the environments shapes the individual or the individual shapes their environment – predict the same pattern of results. However, while it is true that adults have autonomy in who is included in their social network, young children have considerably less autonomy. Most of children's social networks in the first few years of life reflect parent childcare decisions. It is certainly also true that characteristics of the child will influence parents' decisions about childcare; however, external events in early childhood, such as the onset of formal schooling, can offer natural experiments to ask how 1) environments change as a result of the external event and 2) the extent that these changes are related to child outcomes. With the proper experimental design, future work can explore this possibility.

Future Directions

Social network research can be broken down to research questions that study network variables as predictors, outcomes, or both – this produces 3 distinct theoretical approaches to the study of social networks (Borgatti & Halgin, 2011; Perry et al., 2018). Network variables as predictors has been the focus of this dissertation and much of the theoretical argument outlined in the Introduction; however, these other theoretical network approaches can be used to generate cutting edge questions for the field of developmental science.

Studies that explore network variables as outcomes ask questions about how a non-network variable leads to the formation of the social network. For example, do parents' values about diversity relate to the racial make-up of children's network? Do parents' values about diversity have an indirect effect on children's racial bias as a result of the child's social network? How do parents' beliefs about family relate to the formation of children's networks? Rather than focusing on how network properties might relate to social cognitive development, questions under this theoretical approach can be used to ask questions about how non-network aspects of early social experience (such as input or attending formal school) might relate to the formation of certain social networks characteristics.

Studies that explore network variables as both outcome and predictor ask questions about how a network phenomenon relates to another network phenomenon. Research questions that employ longitudinal social network design would fall under this theoretical approach. The studies reported in this dissertation used a cross-sectional approach to explore how network properties at a moment in time related to social cognitive development. Although there is obvious value in using social networks in a cross-sectional design, social networks are an exceptional tool to ask about how *changes* in network properties relate to *changes* in cognition or behavior. For example, the cross-sectional analysis showed that child age was correlated with network size. Is it the case that as children get older, their network size increases? What network properties change after children enter out-of-home childcare? Do changes in the racial outgroup members in the network relate to children's emerging racial bias? These are all questions that can be answered using *The Child Social Network Questionnaire* in a longitudinal design.

These are just a few examples to highlight the myriad of questions that developmental scientists can generate using a social network perspective. Social networks are a previously unexplored dimension of early social environments in early childhood, but the data presented here provide an initial step to better understand how variations in early social experience relate to social cognitive development.

Conclusions

In conclusion, social networks are an exceptional and underutilized tool in developmental science to study social phenomena. Social networks are a method that can capture and describe early social environments and it is a generative framework to ask novel, innovative questions about how variations in early social experience relate to social cognitive development. Social network theory can be used in developmental science to extract the cognitive value of young children's social relationships.

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Appendix A: Parent Interview Manual for The Child Social Network Questionnaire

The **Social Network Survey** has two parts. The first part is a parent interview where parents describe their child's "typical week" of activities. This interview generates the people or 'nodes' in the child's social network. The second part of the survey collects demographic information for each of the people mentioned. Below is a detailed guide on how to conduct the parent interview. These are prompts to use after you explain how the survey is going to work.

Intro: "Before I have you describe [CHILD'S NAME] typical week, can you tell me who are the people that live at home?"

- Questions you might get in response to this:
  - "They have an older sibling that doesn't live at home anymore"
    - siblings should be included in the network
  - "We are a military family and their [mom/dad/step-mom/step-dad] is away right now"
    - That person should be included in the network. This is only true for Mom/Dad/step-mom/step-dad.
  - "My child lives in two different homes" – this happens when the child's parents are not together. Depending on their response is how you proceed:
    - If the parent **can** tell you about their child's experience in the other home – who lives there, who the child sees when they are with the other parent – you can proceed with the interview.
    - If the parent **cannot** tell you about their child's experience in the other home or says something like "I couldn't tell you" or "I only have them on weekends", then you need to void the survey – you cannot be confident in this network data.
  - "Their grandma lives with us 6 weeks out of the year, but isn't here right now."
    - **Do not include** this person. The interview has to be conducted for the people the child sees **on a weekly basis**. The military family example is the only exception to this rule.

Next prompt: "Great, thanks! Now I want you to think about [CHILD'S] schedule Monday through Sunday – what does that look like for [HER/HIM] and what kinds of activities are they doing?"

- At this point, you will find out if the child is in daycare/preschool or not. If they are in daycare/preschool, this is the first things parents will tell you.
- **If they are in daycare/preschool:**
  - **"**How many teachers do they have at preschool?"
    - Questions that parents will ask in response to this question:
      - "Does the music/art/gym teacher count?"
        - If they see the music/art/gym teacher every week, then that person is included.
      - "They have 2 teachers and a teacher aide."
        - The teacher aide is included.

                • "We go to a preschool where there is no set teachers – it is a lot of parents and adults and they change every week."
                    ○ Ask who were the adults that their child knows that they saw the previous week (this response is extremely rare – in over 300 interviews, this response happened once).
    ○ "Thinking about the kids in the class, is there anyone that stands out as a friend?
        ▪ Questions that parents will ask in response to this question:
            • "They are friends with everyone."
                ○ This is not true (and something we know from the Network literature – people are bad at representing their own networks). Do not disagree with the parent. Instead, ask, "Great, can you tell me their names?". Parents will then produce a list of 1-5 friends on average. These children should be recorded as "friends" in the survey. See below about how this is a methodological choice in how the survey is conducted.
            • Kids in daycare/preschool will be it's own node.
            • "I couldn't tell you" / "You're talking to the wrong parent":
                ○ This is what I call the "doofy dad". If you can get to the parents who can answer this, switch gears and interview them. If you cannot get the friends names, you have to exclude.
                ○ Importantly, this is different than "they have this new friend, but I can't remember their name". That is **okay**. You can say "just give us a name or I can leave them in here as "Friend 2" and you'll know it is this person".
- **If they are NOT in daycare/preschool:**
    ○ They will typically start describing their day with a primary caregiver (we read books, play with toys, etc). If they mention a person that wasn't someone who lives at home ("they go to their Grandma's house and see their cousin") **make sure you include those people**.
    ○ If they go to a class every week, it will get mentioned here. See the next prompt for how extract those nodes.

Next prompt: "Great, thanks! Again, thinking about their schedule during the week and weekend, is there any other class or activity your child does every week? Either formal or informal - soccer or something like that?"

- Follow the same procedure as daycare/preschool. For each activity they list, you should ask:
    ○ "How many teachers/coaches do they have at [ACTIVITY]?"
        ▪ Questions parents will have in response to this:
            • "They have 4 coaches, but they change every week"
                ○ Ask them who they saw the last time they were at the activity.
    ○ "Thinking about the kids in the class, is there anyone that stands out as a friend?

            - If they mention a friend from a different context “the friend Jason they have at preschool is also in basketball”, you already have that marked, so you do not need to mark it again.
            - “Kids from [ACTIVITY]” should be it’s own node

Next prompt: “Do you have extended family that you see on a WEEKLY basis?”

- Questions you will get in response to this:
    - “We see them once a month”
        - Do not include. They have to see them weekly or at the very least biweekly.
    - “We skype with Grandma every week”
        - If it is every week, then you should include this person.
    - “Yeah, we see them once a week or every other week.”
        - Include them.

Next prompt: “Great, so again thinking about [CHILD’S] typical week, is there anyone else that you think is worth mentioning?”

- Here is where I most often get “neighbors” and “family friends”. Parents will ask “Do you want the adults too?” IF they see the adults on a weekly basis, then yes!
- If this person they mention is a friend of their child, put the person in as a “Friend”. Put anyone else as the “Other” node.

Appendix B: Laboratory Demographic Form for The Child Social Network Questionnaire

Demographic Form

Name:___________________________________

Race (circle all that apply):

African or African-American   Asian or Asian-American

European or White-American   Hispanic or Latino-American   Native American

Mixed/Biracial

Other:______________________________

Gender:

Female   Male   Other:______________________________

Age: _____________

How many/which languages does this person speak? Do they speak directly to the child in all these languages?

Please circle the categories that your child does with this person:

Eats meals with child.

Caretaking (changes clothes, bathes, etc.)

Play activities (plays with toys, watching TV, etc.)

Traveling outside the home (errands, grocery shopping, pick up siblings, etc.)

Outings (go to the park, museums, etc.)

Please write YES or NO to the following questions. There is space below if you feel the need to elaborate.

- When your child is in distress, will they accept comfort from this person?
- Does your child know this person's name?
- Do they talk about this person if the person is not present?

- Will your child leave with this person (if this person came to your house and say “let’s go out and play”?)

Appendix C: Museum Demographic Form for The Child Social Network Questionnaire

<u>Museum Demographic Form</u>

What is this person's gender?

- ○ Male
- ○ Female
- ○ Both
- ○ Other ________

What is this person's age?

- ○ Child (0-12)
- ○ Adult (13+)

What is this person's race? (Please select all that apply)

- ☐ African or African-American
- ☐ Asian or Asian-American
- ☐ European or White-American
- ☐ Hispanic or Latino-American
- ☐ Native American
- ☐ Mixed/Biracial
- ☐ Other: ________

Q16

How many languages does this person speak?

- ○ Speaks only English
- ○ Speaks only one language (not English)
- ○ Speaks more than one language
- ○ Preverbal

Carry Forward Choices
Selected Choices - Entered Text from "Select the child's clusters"

Q431

In what settings do they interact with your child?

- ☐ » Family
- ☐ » Preschool/Daycare
- ☐ » Extracurricular 1
- ☐ » Extracurricular 2
- ☐ » Extracurricular 3
- ☐ » Extracurricular 4
- ☐ » Extracurricular 5
- ☐ » Extracurricular 6
- ☐ » Extracurricular 7