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YOUNG ADULTS' CLOSE SOCIAL RELATIONSHIPS MAY INFLUENCE FACE RECOGNITION ABILITIES

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ABSTRACT

Individuals differ in unfamiliar face recognition abilities, both in typically developing and in clinical samples. However, it is unclear why such differences emerge across development. Clinical research indicates that individual differences are related to individuals' ability to maneuver through their day-to-day social context and form relationships with others. My previous research with typically developing emerging adults indicates that individuals who are poor recognizers have larger networks and more social support, which is in opposition to the clinical literature. To explore this surprising finding further, I developed a project incorporating social connectedness, which incorporates a more qualitative assessment of what a participant's relationships mean to them. Following the body of research investigating connectedness and the need to belong, I expected that the degree to which participants experience connectedness would be negatively associated with their recognition ability, due to a motivation to find new connections among those with low connectedness. In a sample of 130 young adults ranging from 18 to 28, I found an interaction between connectedness and support such that participants with low levels of connectedness and low support favored face recognition over object. These results indicate that social information processing can be affected by participants' existing social contexts.

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Chapter 1

Introduction

Recently, research in face processing has begun to evaluate the degree to which individuals vary in their ability to recognize faces. This variability in the ability to recognize faces may have profound implications for social interactions, including the ability to predict another's behavior and determine appropriate responses. For example, mistaking the face of a stranger for that of a loved one could result in confusion, embarrassment, and a lack of security in the relationship; consistently mistaking or failing to recognize important faces could even potentially result in dangerous outcomes. As such, the importance of understanding the nuances underlying such individual differences in face recognition has recently rose to the forefront of face recognition science.

The range of individual differences in face recognition abilities among typically developing adults is notable. For example, super-recognizers have exceptionally good face recognition skills (Russell et al., 2009) and exhibit stronger neural activation when observing faces (Elbich & Scherf, 2017). On the other hand, there are individuals who have exceptionally poor face recognition ability despite normal vision and the absence of brain damage or other cognitive deficits (congenital prosopagnosia; Behrmann et al., 2005). Finally, there are individuals with exceptionally poor face recognition skills without a prosopagnosia diagnosis (Elbich & Scherf, 2017).

Understanding the antecedents of these individual differences in face recognition ability is complex. There is evidence that multiple factors play a role, including genetic heritability (Wilmer et al, 2010; Shakeshaft & Plomin, 2015), exposure to hormones (Leow & Davis, 2012; Bate et al., 2014), efficacy of neural processing (Elbich & Scherf, 2017; Ramot et al., 2019), strategies for recognition (DeGutis et al., 2013; Wang et al., 2012; Bennetts et al., 2017), experience (Chua & Gauthier, 2019; Sunday et al., 2018; Balas & Salville, 2015), and personality factors (for example, Rigby et al., 2018). Recognition researchers have also hypothesized that the face recognition system reflects social motivations and contexts, including the need to fulfill important developmental tasks, at least partially governed by puberty, by facilitating close bonds with caregivers and peers among children and adolescents respectively (Scherf & Scott, 2012; Picci & Scherf, 2016; Scherf et al., 2012). Finally, there is evidence in clinical samples as well. In autism, prosopagnosia, and schizophrenia, deficits in social behavior are associated with deficits in face recognition (Maher et al., 2016; Griffin et al., 2021; Grelotti et al., 2002; Yardley et al., 2008; Bortolon et al., 2015). These findings lead to a clear hypothesis that individual differences in social behavior map on to variations in face recognition abilities. However, support for this hypothesis in typically developing samples is not yet significant.

To address this gap in the literature, I evaluated whether characteristics of participants' social network structure and their sense of connectedness within these networks are related to how well individuals recognize faces. Specifically, I determined whether network size, the quality of relationships in the network, and the sense of connectedness generated from the network's properties are systematically related to face recognition abilities in young adults (ages 18-28 years). This is a developmental period when social networks are potentially in flux, specifically for emerging adults between 18 and 25 years of age, who begin to branch out and build lasting relationships (for example, Subrahmanyam et al., 2008), and when face recognition abilities are still improving (Germine et al., 2009). This project was also conducted during the COVID-19 pandemic when the structure and composition of social networks and self-reported connectedness may have been in flux for many individuals because of the precautionary measures that restricted in-person social interactions.

The Potential Association between Social Behavior and Face Recognition Ability

As previously described, children and adolescents' abilities to form important relationships with caregivers and peers is differentially reflected by biases in the face recognition system (Scherf & Scott, 2012; Picci & Scherf, 2016). In adults, high levels of empathetic behavior and personality traits related to extraversion are associated with stronger recognition skills (Rigby et al., 2018; O'Reilly & de Haan, 2009; Li et al, 2010). Similarly, the tendency to see overlap between one's sense of self and close others is linked to face recognition ability, while high levels of social anhedonia are associated with poor recognition ability (Ketay et al., 2019; Germine et al., 2011). Further, there is evidence that both connectivity in and the size of the amygdala, a region implicated in face processing, is related to the size of humans' social networks, suggesting that the propensity to develop relationships is an ability at least partially grounded in similar neural mechanisms as face processing (Bickart et al., 2012; Jones et al, 2020). In sum, this research suggests that face recognition ability may be related to certain components of one's social relationships, potentially as indexed by the degree to which individuals connect with others.

Thus, there is mixed evidence for an association between face processing ability and social behavior related to being in relationship with others. Based on this evidence, one might reasonably predict that those who have larger or more connected social networks would be better face recognizers. To this end, in a previous study, I collected data regarding the social network properties and unfamiliar face recognition abilities of 65 emerging adults. These properties included social network size, indexed by three different degrees of closeness, the duration of each relationship for the self-reported closest members of participants' networks, and the frequency of contact with these close members (Antonucci & Akiyama, 1987; Norbeck et al., 1981). In contrast to predictions, I found that the size of participants' most intimate circle of relationships, and not the size of their overall network, was negatively associated with face recognition performance. Specifically, individuals who nominated larger close networks exhibited worse face recognition. Frequency of contact with the closest members, as well as contact with members regardless of closeness, were both negatively related to face recognition. Thus, this research indicates that structural components of social networks, including size and frequency of contact, are negatively related to recognition ability, challenging the established prediction.

It is also possible that instead of network structure, relationship closeness or the sense of relational intimacy might relate to face recognition ability. Even further, a multitude of relationships may not necessarily reflect the existence of strong intimate relationships. For example, some individuals may build social networks that are populated with many connections, but with fewer strong connections, while others may build networks with fewer connections, but a strong intimate ties (King, 2021). How might differences in these kinds of networks, and the sense of intimacy they generate, relate to face processing?

I first addressed this question using a measure of social support to index relationship intimacy. Previous research has indicated that the overall size of participants' networks is indeed unrelated to face recognition; instead, the degree to which participants have many close relationships is positively related to recognition (Engfors et al., 2018). To investigate this further, I returned to the sample of 65 emerging adults and investigated whether social support from close network members is related to unfamiliar face recognition using the Norbeck Social Support Questionnaire, following Engfors work (2018; Norbeck et al., 1981). Surprisingly, social support from close network members was negatively related to face recognition, suggesting that those with lower levels of support were better at recognizing faces. This contrasts with research that indicates that the degree to which participants connect with others is positively related to recognition.

Next, to alternatively operationalize this sense of intimacy and strength of relationships, I investigated how positive and negative qualities of familial and peer relationships may be associated with face recognition in a sample of 115 emerging adults. Participants completed the Network of Relationships Inventory (NRI), which evaluates positive (i.e., companionship and affiliation) and negative (i.e., conflict and antagonism) qualities within a predefined set of four familial relationships (mother, father, sibling, other relative) and three peer relationships (same-sex friend, other-sex friend, past or present romantic partner) (Furman & Buhrmester, 1985). Following the hypothesis that face recognition serves to facilitate relationships with others, I expected that positive relationship quality would be positively related with face recognition. Yet, I found that positive relationship quality was not associated with face recognition ability. Instead, negative quality was positively associated with face recognition abilities. In other words, those who reported more conflict with family or peers performed better recognizing unfamiliar faces, again in contrast with research suggesting that connections with others are positively associated with face recognition.

These findings add further evidence to the hypothesis that the structure, organization, and quality of social networks might dynamically shape face recognition abilities. However, the direction of the association is opposite to the purported hypothesis. Rather than reflecting the idea that a large network and close relationships reflect adept recognition skill, this data instead suggests that face recognition is best under conditions of weak relationships or smaller networks.

Further, while the measures of support, positive relationship quality, and negative relationship quality reflect the quantitative occurrence of certain behaviors, and network size reflects the number of relationship partners, these variables may not reflect how connected a participant may feel due to the important relationships in their life. For example, a relationship high in conflict and antagonism may reflect a strong bond between two partners, just as a relationship high in support. Further, participants with only one source of support may feel just as socially satisfied and connected as those with several different sources of support. In addition, these measures reflect the characteristics of only a few of participants' relationships, and do not a global sense of connection across a participant's network. Thus, both the surprising findings and the nature of the assessments used predicate the use of a new measure that might better capture the degree to which participants connect with others.

Social Relationships and Connectedness

In social behavioral research, such investigations about the nature and quality of an individual's social context often incorporate a measure of the belonging or connectedness derived from their relationships. While related to other constructs like attachment, support, and loneliness, feelings of belonging and connectedness function as a higher-order representation of the need to find fulfillment in one's relationships (Lee & Robbins, 1995). Lee and Robbins, the authors of the Social Connectedness Scale (SCS), describe social connectedness as developing during adolescence, and maintained through emerging adulthood (1995). Connectedness is a specific component of belonging, which refers to the need to both develop independence and find companionship with others, including fostering strong friendships and romantic partnerships in emerging adulthood. As suggested by the authors, a person low in connectedness may feel distant from others, find difficulty accepting certain social roles, and trend towards isolation and loneliness. This need to belong is unique among motivators of human behavior. In Maslow's Hierarchy of Needs Model, the need to belong is one of the five most central motivational drivers of human behavior; if this need to connect with others is not met, individuals' self-concept and self-actualization may suffer greatly (Maslow, 1943). In Self-Determination Theory and Basic Psychological Need Theory, the need to relate to others is one of three universal central drivers of behavior, and threats to this need target an individuals' sense of self (Deci & Ryan, 2000; Maarten et al., 2020). As such, there is strong empirical literature to suggest that connectedness is relevant to social information processing.

Social connectedness opens the door to understanding how participants view their relationships, beyond the amount of support or conflict in their relationships, or the size of their social network. As Lee and Robbins describe, support reflects an individual's outer environment, while connectedness reflects one's inner environment by encapsulating their concept of their social environment (Lee & Robbins, 1995). Lee later refers to connectedness as an attribute of the self that reflects “cognitions of enduring interpersonal closeness” (Lee et al., 2001). In other words, connectedness provides insight into a participant’s reflections about their social network and relationships. For example, connectedness is often studied alongside measures of social satisfaction and satisfaction with social support (Trepte et al., 2015; Inose & Yeh, 2003). It is also important that connectedness is not necessarily dependent on network size; an individual with only one strong relationship could feel just as connected as an individual with several strong relationships. In summary, connectedness reflects the feelings an individual has about their network at large in relation to the need to belong.

Put simply, the degree to which individuals experience connectedness among their network shapes their social well-being (Kesler & Wann, 2020). For example, social connectedness and satisfaction with one’s social support can offset acculturative stress in international students adjusting to a new context, or the stress that emerging adults may experience when beginning college in an unfamiliar context (Inose & Yeh, 2003; Whillans et al., 2017; Whillans & Chen, 2018; Lee et al., 2002). Similarly, connectedness with one’s family or ethnic heritage, community, or school can offset decreases in well-being across development, moderate the impact of discrimination, influence behavioral outcomes like substance use, and shape satisfaction and self-esteem (Stuart & Jose, 2014; Wei et al., 2012; Yang et al., 2014; Witherspoon et al., 2009; Rose et al., 2019). Connectedness and satisfaction with one’s support have also been found to be related to collective self-esteem, subjective well-being, happiness, depressive symptoms, state-trait anxiety, and occupational well-being (Lee & Robbins, 1998; Lee et al., 2008; Minkkinen et al., 2016; Lombardi et al., 2019; Lee & Choi, 2013). Thus, this research suggests that those who lack connectedness to their network may experience social dissatisfaction.

Given the importance of experiencing connectedness, individuals would seek to remedy a lack of connectedness by finding new relationships with others. As such, connectedness particularly relevant to face processing. Much of this literature comes out of investigation of the merits of offline rather than online interaction; generally, face-to-face interaction can improve feelings of connectedness and belonging (Sacco & Ismail, 2014). Interestingly, the quality of these interactions matters, as negative face-to-face interactions can thwart feelings of belonging (Ringer & Anestis, 2018). The target of the interaction also is influential, as interaction with a babyish face facilitates belonging to a greater degree than interaction with mature faces (Sacco et al., 2014). In other words, connectedness functions alongside the existence of close relationships with people deemed socially important.

Most relevant for this project, three studies in particular stand out in demonstrating the potential link between connectedness and individual differences in face recognition ability. One study found that ostracism, as generated by experimental design, heightens perceptual sensitivity to facial signals of acceptance or rejection, as well as sensitivity to ethnic-racial facial categories, theoretically driven by a need to identify affiliative allies (Sacco et al., 2011). Similarly, in another study, White participants who indicated higher levels of a need to belong, which suggests that their need has not been met, and participants who were exposed to threats to their social belonging, were more likely to categorize ambiguous faces as Black (Gaither et al., 2016). Finally, in a direct study of face recognition, participants with a higher need to belong, as well as participants who were exposed to a threat to their belonging, were better at recognizing unfamiliar faces from their own social group relative to out-group faces (Van Bavel et al., 2012). This finding accompanies research highlighting a general bias against out-group faces, theoretically driven by a social preference for people within one's own ethnic-racial group (Ferguson et al., 2001; Hugenberg et al., 2010). Thus, this may suggest that those low in connectedness are biased to look for and seek relationships with others and use recognition of unfamiliar faces to facilitate these new connections.

These three studies suggest that face recognition is particularly useful in conditions of low connectedness, theoretically allowing individuals to seek new relationship partners. However, it is important to point out that these three studies have focused on a particular subset of faces, distinguishing between ethnic-racial in-group recognition and out-group recognition. As a result, it is unclear whether this finding extends to faces in general; that is, do those low in connectedness exhibit better general unfamiliar face recognition in effort to form new relationships to bridge the gap in connectedness?

Social connectedness can provide valuable insight into the quality of an individual's social life and social well-being. Assessing connectedness offers insight into whether participants' need to belong is being met, which thereby may offer insight into their motivations regarding social behavior (Maslow, 1943). As a construct, it demonstrates some overlap with measures like social support while also going further to assess the way an individual values, appreciates, or benefits from their relationships. In seeking to understand how face recognition reflects a motivation to find connection with others, connectedness offers a way to assess the degree to which that motivation has been addressed. As such, social connectedness could provide insight into the importance of individual differences in face recognition abilities. The intricate tie between connectedness and the kinds of networks that individuals build may very well influence their motivation to find new points of belonging with others, as may be indexed by unfamiliar face recognition ability. In other words, connectedness may vary in a similar pattern as unfamiliar face recognition. Further, connectedness could provide insight into the findings that compare unfamiliar face recognition to social support, social conflict, extraversion, empathy, and more.

Current Study

In summary, there are several potential ways social relationships may intersect with face recognition ability. Generally, empirical work suggests that connection with others may be associated with face recognition; however, the exact mechanisms of this association are unclear.

In theory, the existence of strong bonds and connection with members of a specific group in a participant's network would bias recognition towards those faces; still, it is worth questioning whether this is to the detriment of recognition of unfamiliar people who are not in a participant's important network. Thus, the next phase of research uncovering the nature of face processing abilities should specify the nature of this association. What does an understanding of social connections add to the understanding of how face recognition abilities develop and differ?

The following overarching question guided this study: *In what ways are characteristics of participants' social networks associated with face recognition abilities?* In this current study, I used the variables of social network size, social support, social discord, and global connectedness to answer this question. These variables also guided my primary analytic questions.

First, I asked: *Is the connectedness participants experience associated with face recognition ability?* In answering this question, I sought to replicate findings from my previous research, thereby asking: *Are network size, social support, and conflict and antagonism related to face recognition ability?* Third, I asked: *Does connectedness interact with network size, social support, or conflict and antagonism in relation to face recognition?* Finally, I asked: *Do the effects of the social behavior variables differ between face and object recognition?*

There were two alternatives for my first hypothesis. The clinical research hypothesis suggests that those who experience difficulties in social contexts are also likely to be poor recognizers (Maher et al., 2016; Grelotti et al., 2002; Yardley et al., 2008). If connectedness reflects participants' global sense of their network, one might expect that those with higher levels connectedness have had more success forming relationships with others, and would therefore have better face recognition, whereas those with lower levels of connectedness would experience difficulties connecting with others. This is also in keeping with the predictions made by Lee and colleagues (1995, 2001), as those who are low in connectedness face difficulty finding new connections and exhibit interpersonal dysfunction that may limit their ability to connect. This may result in worse face recognition abilities because of an overall smaller set of individuals to keep track of (Engfors et al., 2018). As a result, this research, under what I refer to as the Clinical model, suggests that there is a positive association between face recognition and connectedness. Specifically, this model predicts that individuals who exhibit lower levels of connectedness also exhibit poor face recognition performance, potentially due to less visual input to tailor their recognition ability, and/or an innate dysfunction in connecting with others.

On the other hand, research with typically developing samples, including the study by Van Bavel and colleagues (2012), emphasize how a motivation to find belonging with others positively influences face recognition abilities. If a participant's need to belong has not been met, they might experience a strong motivation to address that need, and thus be inclined to connect with those who they may not know. Therefore, one may expect that those low in connectedness would be motivated to identify new relationship partners, and as a result, exhibit better unfamiliar face recognition. In addition, my own previous research suggests a negative relationship between recognition and support, and recognition and network size, and positive between conflict and recognition. If there is a complementary relation between relationship quality, network size and connectedness, one may expect the negative relationship between the former variables and face recognition to extend to the relationship between connectedness and recognition. Thus, under what I refer to as the Need to Belong model, research indicates a negative association, theoretically suggesting that unfamiliar face recognition best for people who lack connection and have a need for belonging that is currently unfulfilled.

Given that Van Bavel's research directly tested face recognition, my hypothesis for the first question followed the conclusions from that study. *Specifically, I hypothesized that face recognition will be negatively associated with social connectedness, such that those low in connectedness will exhibit better unfamiliar face recognition.* In this way, participants who have satisfied their need for connectedness perform worse on tests of unfamiliar face recognition.

Question Two further investigates the diverging findings from my two previous findings in a new and larger sample. Social support, social discord, and network size assess structural characteristics of participants' networks, including the occurrence of certain behaviors and the number of connections, in contrast to connectedness. Thus, I collectively refer to these variables as structural measures of social behavior (see Appendix F). *Following my previous research, I expected to replicate the finding that individual differences in these structural variables are related to individual differences in face recognition abilities, specifically that support and network size are negatively related to recognition, and conflict is positively related.*

Third, I have previously discussed how connectedness is not necessarily dependent on network size, support, conflict, or antagonism. Given this construct independence, one might reasonably predict no interaction; for example, the effect of support would not vary by level of connectedness. In effect, connectedness would remove any of the variance due to support, size, and conflict and antagonism.

On the other hand, connectedness could play a buffering role against the potential detriment of having low levels of support or high levels of conflict and antagonism. In this case, a significant interaction would reveal that the effects of size, support, and conflict and antagonism are seen only in cases of low connectedness. This model is supported by findings regarding how connectedness functions in acculturative stress in new contexts (Inose & Yeh, 2003; Whillans et al., 2017; Whillans & Chen, 2018). Given my findings about network size, support, conflict, and antagonism, and my expected association between connectedness and face recognition, I predicted an interaction as previously described. *I expected that the effects of the structural social behavior variables on face recognition will be evident only in cases of low connectedness.* In such a case, I again expect negative associations between support and face recognition and size and recognition, and a positive association between conflict and recognition.

To summarize these hypotheses, I expect that lower levels of connectedness is associated with worse face recognition performance. If this hypothesis is true, this suggests that unfamiliar face recognition is less important for those who have strong relationships with important people in their lives. In this case, individuals focus their processing on the faces that are most important to them, to the detriment of recognizing unfamiliar faces. On the other hand, young adults who do not feel connected to others will likely seek connection from others who are not currently in their network. Thus, these participants will exhibit better recognition of unfamiliar faces. All in all, these results would suggest that face recognition abilities vary by the relationships individuals have, highlighting its value as a key component in social interaction and social behavior.

Chapter 2

Methodology

Participants

In an a-priori power analysis using G-Power software of my primary model (Model 1), I specified a small effect size (Cohen's $d = 0.24$), a standard alpha rate ($\alpha = 0.05$), power of 0.80, and seven tested predictors along with two control variables (Faul et al., 2009). Based on the results from this analysis, I intended to recruit at least 127 eligible participants. For ease of analysis, I therefore sought 130 participants to match participants on gender.

Participants were recruited using the Cloud Research platform, which recruits participants using Amazon Mechanical Turk (Litman et al., 2017). In the final sample, I screened 541 participants in total, and recruited a full sample of 140. To match participants on gender, I selected 65 men and 65 women for the analytic sample of 130 to reach the power requirement previously described. Demographic information for the analytic sample is presented in Table 1. Participants were emerging and young adults, ranging from 18 to 28. Many emerging adults have entered a period in which they face important developmental tasks, including establishing independence while also developing strong friendships and romantic partnerships. Thus, this makes their social relationships of empirical and developmental interest due to their unique social context.

Table 1. Demographic Characteristics of Sample.

	Total Sample	**Men**	**Women**
N	130	65	65
Age (years)	24.05	24.10	24.00
Percent White	54.62%	56.92%	52.31%

In my previous research, I was able to recruit emerging adults specifically, primarily by recruiting Pennsylvania State University undergraduate students. However, in this study, I recruited online, and found it difficult to recruit within the specific emerging adulthood developmental age range of 18 to 25 in a timely manner. As a result, I expanded my sample to include young adults more broadly, up to 28 years old. Even still, it is important to note that a significant portion of this sample (35%) are outside of the typical emerging adult age range, as will be discussed throughout this manuscript.

Written informed consent was obtained using procedures approved by the Internal Review Board of the Pennsylvania State University. Participants were recruited through Amazon Mechanical Turk. In the screening, participants answered questions about history of neurological (e.g., Parkinson's disease, Huntington's disease) or psychiatric disorders (e.g., mood, body dysmorphic, anxiety, and developmental disorders) in themselves or their first-degree relatives. Participants with no such history were then invited to the study.

Measures

Cambridge Face Memory Test

Participants first completed the recognition tasks. To collect the recognition data for this study, I utilized the Psychopy, Pavlovia, and Gitlab resources (Peirce et al., 2019). To assess face recognition, I used the long form of the Cambridge Face Memory Test (M-CFMT+) (Duchaine and Nakayama, 2006; Russell et al, 2009). While the task only uses White male faces, it compares well to other tests with different facial stimuli, including female faces (Scherf et al., 2017; Arrington et al., under review). The task consists of 102 trials, split over four blocks that consecutively increase in difficulty (see Appendix). Participants are introduced to six male target faces in the first block and are trained to recognize these faces among distractor faces. In the proceeding blocks, participants are tasked with recognizing the target faces under certain conditions, including novel images, images with noise, and images with emotional expressions.

Cambridge Car Memory Test

I also implemented a control test by using the Cambridge Car Memory Test to assess object recognition (Dennett et al., 2012). The CCMT proceeds in the same way as the face task but consists of only three blocks and 72 items. I randomized the order of the two tasks across all participants.

Social Behavior Questionnaire

Network Map. To assess network size and composition, participants completed a social network map allowing them to place every important person in their life (Antonucci & Akiyama, 1987). The network map contains four concentric circles, with the inner-most representing the participant, and each outer circle representing different levels of intimacy network members have with the participant. Participants had 10 minutes to write the initials of up to 75 people whom they wanted to nominate, for any of the circles. Counts of network members were created for each concentric circle to get individual circle network size. Also, all network members across the concentric circles were summed to get total network size.

After completing the map, participants were asked to nominate their entire inner circle, up to 10 nominees, for additional assessment of network quality. I specifically targeted the inner circle to identify participants' closest relationships, in accordance with research that similarly focuses on participants' closest relationships (for example, Mark & Harris, 2012; Kammrath et al., 2020). If participants had more than 10 partners in their inner circle, they were asked to select those "most important to them". If they had less than 10 in their inner circle, participants were allowed to select those outside their inner circle, up to 10 total nominations.

Norbeck Social Support Questionnaire. Participants then indicated the degree to which they obtain support from up to ten nominees (Norbeck et al., 1981). This measure of support assesses different forms of support, including emotional support, aid support, support by frequency of contact, and support by duration of relationship. Sample items include "How much does this person make you feel liked or loved?" and "If you needed to borrow $10, a ride to the doctor, or some other immediate help, how much could this person help?". Responses ranged from 1, "A Little", to 5, "A Great Deal". Reliability analyses indicated that the measure was highly reliable (α = 0.96). In addition, participants identified the ethnic-racial group membership of each of their nominees, as well as the source of each relationship in accordance with the Network of Relationships Inventory (NRI) (i.e., mother, same-sex friend, etc.). This measure has been used in similarly aged samples, as well as samples that have experience some degree of recent trauma, such as refugees and those recently bereaved by suicide (Brittian et al., 2009; Rode et al., 2018; Kingsbury et al., 2019; Spino et al., 2016). Thus, its use in this study, during a global pandemic, adds to the existing literature.

I created support scores for Functional Support, Frequency of Contact, and Duration of Relationship, following Norbeck's original work (1981). Frequency and duration are each one item, while functional is the sum of six items (two items each for Affection, Affirmation, and Aid). In comparing the kinds of support to each other, I found a large degree of overlap (see Table 2). Thus, I focused on and report the findings pertinent to functional support, given that functional support provides information about the behaviors that exist within a relationship in a way that frequency and duration do not.

Given that support scores are summed, participants who nominated more network nominees, or selected more nominees in their questionnaire, may implicitly have higher support scores. This procedure follows Norbeck's original work (1981). In theory, this approach can be thought of as measuring individual differences in the amount of support resources participants have available, as Norbeck suggests in her work by referring to the network "convoy". For example, functional support contains indices for emotional support and aid support. Higher scores in these metrics indicate that a participant has more support resources available, whether due to the nature of the relationship, or to the amount of relationships. The alternative measurement approach would be to use averaged scores instead of summed scores. By way of comparison, I also created averaged support scores by dividing the summed scores by the number of nominees (out of ten), where each score indicates the amount of support an average nominee contributes to the participant. However, these scores are heavily skewed (functional: -0.96; frequency: -1.02; duration: -1.93). In addition, this measure does not account for the total amount of support resources available to the participant, therefore being biased against participants with larger networks, as noted by Norbeck herself (1995). To properly account for the idea of a network convoy by adjusting for network size, I applied the summed score approach instead of the averaged score approach.

Network of Relationships Inventory. Using the NRI, I also assessed the negative quality of relationships with the participants' nominees, henceforth referred to with the variable name "discord". The NRI (Social Provisions Version) uses two subscales consisting of three questions each (Furman & Buhrmester, 1985). Sample items include "How much do you and this person get upset with or mad at each other?" and "How much do you and this person get on each other's nerves?". Responses ranged from 1, "Little or None", to 5, "The Most". Discord is the average of six items regarding conflict and antagonism, across each nominee; Cronbach's alpha indicated high levels of internal consistency when using this approach ($\alpha = 0.93$). Thus, in contrast to the support scores, scores on the NRI indicate how much conflict a participant experiences with each person in their network, in accordance with Furman and Buhrmester's work and recommendation (Furman & Buhrmester, 1985; Furman & Buhrmester, 2010). This is typically used to compare participants' relationships to each other, but in this study, I use these scores to assess the average level of discord in participants' relationships. Previous studies have focused on these six items in their use of the NRI, including in similar samples (Lazarevic et al., 2021; Mastrotheodoros et al., 2020; Jouriles et al., 2021; Thompson et al., 2020). Due to skew in the data resulting from participants indicating lower levels of discord, I applied a logarithmic transformation of the distribution to use in my analyses.

Social Connectedness Scale - Revised. Finally, to end the study, participants completed the revised Social Connectedness Scale (SCS-R) (Lee et al., 2001). The SCS-R consists of 20 items, 10 coded as positive measures of social connectedness and 10 coded negatively. The measure uses a standard Likert scale ranging from 1, “Strongly Disagree”, to 6, “Strongly Agree”. Sample items include “I feel close to people” and “I see myself as a loner”. Cronbach’s alpha indicated high levels of internal consistency ($\alpha = 0.96$). Data is scored by reverse-coding negative items and summing the score of each item, resulting in a possible range of 20 to 120, where higher scores predict more connectedness. In other words, summing the scale represents connectedness by the degree to which participants lack frustrations in being understood by and feeling connected to others (Lee & Robbins, 1995). This approach in scoring the SCS has frequently been adapted in similar studies to assess levels of connectedness and belonging (McLoughlin et al., 2019; Turton et al., 2018; Rosenthal et al., 2018; Moilanen et al., 2018).

Procedures

Participants began by completing screening. Eligible participants were then invited to the second portion of the study. In the second portion, participants completed the two recognition tasks, the order of which was randomized across participants. Participants then were redirected to Qualtrics, where the completed the network map, the support questionnaire, the discord questionnaire, and the connectedness questionnaire, before completing the study and receiving payment.

Analytic Plan

All analyses were conducted using R software using the R Studio interface (R Core Team, 2019; RStudio Team, 2020). R packages included tidyverse, psych, interactions, and rstatix (Wickham et al., 2019; Revelle, 2020; Long, 2019; Kassambara, 2021). Accuracy (percent correct items) was the dependent measure. Prior to analyses, the data were examined for violations of normality. Due to skew, I log-transformed discord, inner circle size, and total network size to use in analyses. For a full description of the variables, see the Appendix. I used linear regression analyses to analyze the data by assessing the association between face recognition as a dependent variable and the social network characteristics as independent variables.

In my analyses, I operationalized face-specific recognition ability by creating a difference score between face recognition and car recognition, in contrast to my previous studies. To compute this score, I z-scored both car recognition and face recognition distributions to account for differences between the tasks in performance, and then subtracted car recognition from face recognition to get a measure of how a participant fared in face recognition relative to car recognition. In this way, higher scores indicate recognition that favors faces over cars. While this approach does differ from my previous studies, it does have its merits, despite the controversy surrounding the approach (DeGutis et al., 2013). For example, other researchers that have used this difference score approach have argued that the difference score better accounts for shared variance between car and face recognition (Wang et al., 2012; Gerlach & Starrfelt, 2018). In a study designed to assess individual differences, this benefit adds greatly to assessing differences in face recognition. Henceforth, I refer to this measure as face selectivity.

Scores under this face selectivity distribution better resemble a normal distribution compared to the raw face recognition scores (Figure 1). Thus, in theory, this measure better reveals individual differences in face recognition ability by identifying individuals whose recognition favors faces specifically over other objects, rather than simply identifying individuals who perform well in the face recognition task. As a result, this difference score follows the idea that humans are especially tailored to recognize faces over other objects (Scherf & Scott, 2012). In addition, using the z-scores as the basis for the measure accounts for differences in the tasks, including the difference in number of items.

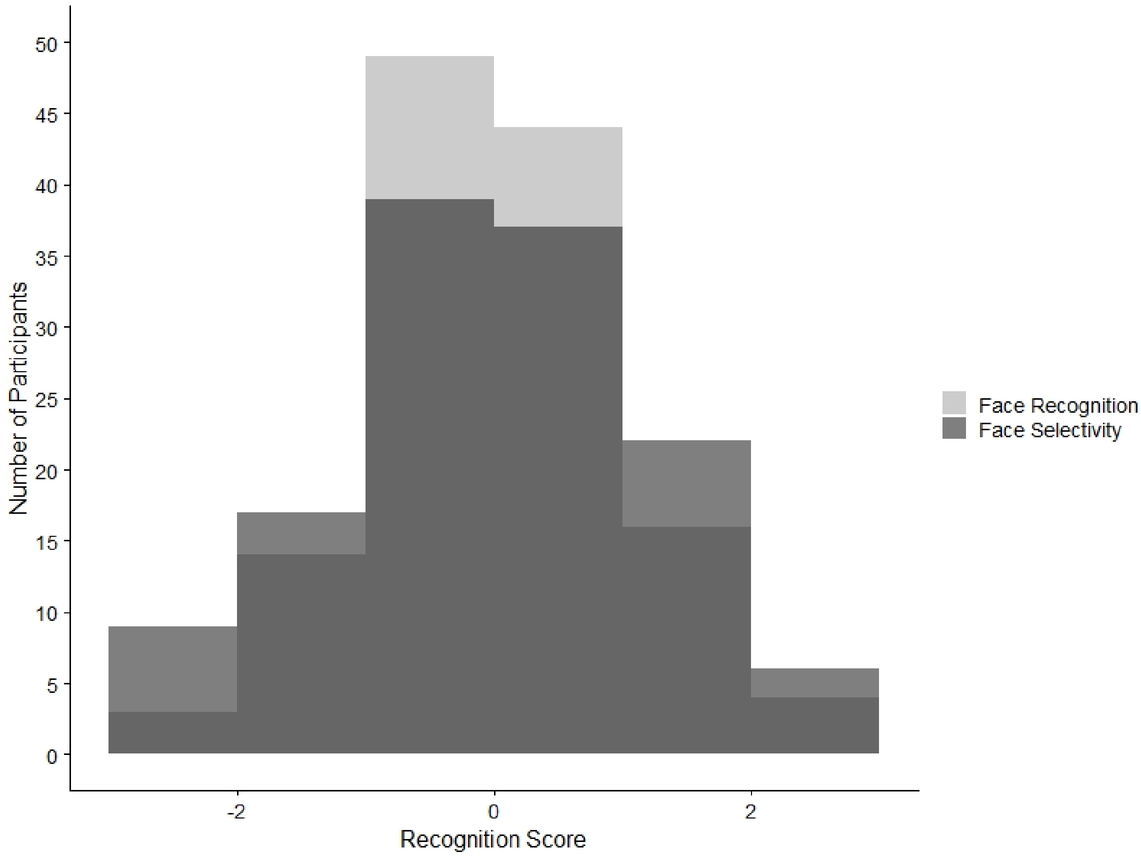

Figure 1: A comparison of z-transformed face recognition scores (light grey), as measured by the CFMT+, and z-transformed face selectivity scores (dark grey), as created by subtracting car recognition from face recognition The face selectivity scores appear to better reflect a normal distribution.

Next, I selected participant age and gender as control variables. As predictors, I included the structural variables of social support, discord, and network size, as well as connectedness, and interactions for each structural variable and connectedness. I computed support and discord in two separate ways. First, I created scores using nominees from participants' inner circle, in accordance with my hypothesis that a participants' most important relationships are significant in contributing to connectedness, as well as pre-existing research that uses a similar approach (Mark & Harris, 2012; Kammrath et al., 2020). For example, in this case, functional support is computed as a function of support from Circle 1 nominees, rather than all nominees regardless of circle, in accordance with my hypotheses. Second, I also computed total support and discord scores that incorporated all the nominees, up to ten, regardless of circle, as part of my exploratory analyses in effort to better assess individual differences. For example, functional support under this approach incorporated nominees from Circles 1, 2, and 3, rather than only nominees from Circle 1. The benefit of the former approach is that it follows research highlighting the importance of participants' most intimate relationships. However, the benefit of the latter is that it more holistically accounts for participants' entire networks, as these scores include network members of varying levels of intimacy. In addition, in the case of support, using total nominations redistributes scores across the entire range of support, theoretically better reflecting a normal distribution (Figure 2). I ran analytical models for each of these different approaches to account for the benefits of both approaches.

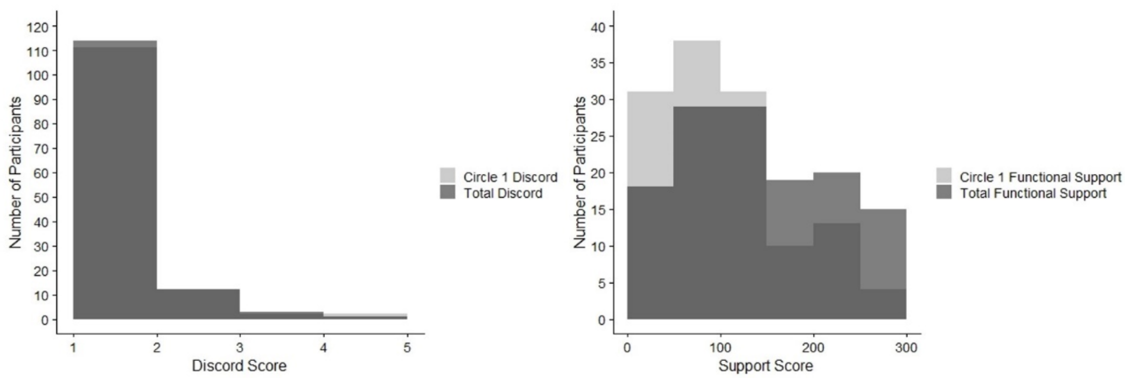

Figure 2: A comparison of score distribution of discord and support between total network scores (incorporating nominations from every circle, dark grey) and circle 1 scores (incorporating nominations only from Circle 1, light grey). In the case of support (right side), the distribution indicates that support scores are better distributed across the range of support when using total network scores, fitting a normal distribution. Since support is summed across nominations, more scores are in the higher range when more nominees are added. On the other hand, conflict remains positively skewed when incorporating all nominees.

For a full list of the models, see the Appendix. To answer Question 1, I created a model that assesses whether connectedness is related to face selectivity over and above the effects of gender and age (Model 1). I expect that connectedness is negatively associated with unfamiliar face selectivity. To answer Question 2, I created three models that assess whether support, network size, and discord are related to face selectivity over and above the effects of gender and age (Models 2-4). Replicating my previous research, I expect that unfamiliar face selectivity is negatively associated with social support and network size, and positively associated with social discord. Finally, to answer Question 3, I created a model (Model 5) that includes face selectivity as the dependent variable, age and gender as covariates, and discord, network size, support, and connectedness as predictors, as well as interactions between discord and connectedness, network size and connectedness, and support and connectedness. In this model, I included each of the structural social behavior variables to test the unique contribution of each variable over and above the other variables. I expect that discord, network size, and support will be significantly associated with face selectivity only in the case of low connectedness.

Results

Descriptive Statistics

Raw face recognition scores resembled those collected in our previous studies (M = 63.51%, SD = 13.00), as did car recognition scores (M = 65.04%, SD = 14.80). In the overall sample, there was no evidence for recognition that favored either faces or cars (M = 0.00, SD = 1.24). On average, participants' inner circle was the largest (M = 5.25, SD = 3.97), accounting for 38% of the total network size (SD = 13%). Circle 2 (M = 4.60, SD = 3.68) and Circle 3 (M = 3.83, SD = 3.21) were both smaller. Total network size averaged at 13.71 nominations (SD = 9.39). Participants selected an average of 6.13 (SD = 3.15) nominees for the support and discord questionnaires.

Participants indicated lower levels of total support than my previous studies ($M_{Functional}$ = 139.65, SD = 77.77, $M_{Duration}$ = 27.52, SD = 15.09; $M_{Frequency}$ = 24.45, SD = 12.73). When the support scores are averaged across the amount of people participants nominated ($M_{Functional}$ = 23.02, SD = 5.00, $M_{Duration}$ = 4.43, SD = 0.72; $M_{Frequency}$ = 4.06, SD = 0.75), scores indicate that support per item per nominee averaged around 4. Discord scores were low ($M = 1.58$, $SD = 0.68$). Connectedness scores reflected a moderate degree of belonging ($M = 76.53$, $SD = 22.52$)

Face recognition was significantly related to car recognition ($r(130) = 0.23$, $p = 0.007$, 95% CI [0.06, 0.39]), but unrelated to age ($t(128) = -1.33$, $p = 0.186$) and marginally associated with gender ($t(128) = 1.71$, $p = 0.089$). Car recognition was related to neither age ($t(128) = 0.84$, $p = 0.405$), nor gender ($t(128) = -0.21$, $p = 0.836$). Given that this sample was older than those of my previous studies, I also assessed whether participant age was related to any of the other variables. Despite a wider age range, network size, connectedness, discord, and support did not vary in association with age ($p > 0.285$).

Correlation Analyses

Before examining the primary models for this project, I examined the zero order correlations using Pearson Product correlations between each of the social behavior variables to determine their relationship. These correlations are presented in Table 2. Discord was negatively related to each of the other variables (correlation range: [-0.14, -0.39]). Each of the support scores were strongly related to each other, reflecting internal consistency (correlation range: [0.91, 0.92]). Given the overlap between each of these three kinds of support, I selected functional support as an index of support, to account for shared variance among the three measures of support. Nominations for each circle were also moderately-strongly related to each other, perhaps suggesting that the larger any one circle is, the more likely it is for a participant to also have large networks in their other circles (correlation range: [0.42, 0.87]). Connectedness exhibited only moderate correlations with the other variables, reflecting the idea that it captures a slightly different aspect of social behavior compared to the structural variables (correlation range: [0.13, 0.43]).

Table 2. Social Behavior Correlation Matrix.

	Connect	Discord	Freq	Duration	Function	Circle 1	Circle 2	Circle 3	Total
Connected	-	-0.43***	0.31***	0.22*	0.42***	0.26**	0.24**	0.13	0.24**
Discord	-	-	-0.32***	-0.32***	-0.39***	-0.23**	-0.24**	-0.14	-0.24**
Frequency	-	-	-	0.92***	0.91***	0.60***	0.47***	0.41***	0.60***
Duration	-	-	-	-	0.91***	0.60***	0.51***	0.45***	0.63***
Functional	-	-	-	-	-	0.65***	0.52***	0.44***	0.65***
Circle 1	-	-	-	-	-	-	0.55***	0.42***	0.82***
Circle 2	-	-	-	-	-	-	-	0.71***	0.87***
Circle 3	-	-	-	-	-	-	-	-	0.80***
Total	-	-	-	-	-	-	-	-	-

Note: N = 130; *p < .05; **p < .01; ***p < .001

Primary Analyses

Question 1: Connectedness

Model 1 tested whether connectedness was related to face selectivity while controlling for the effects of gender and age. Results indicated no relationship between connectedness and face selectivity ($b = 0.00$, $p = 0.920$). Thus, contrary to my hypotheses, there was no relationship between face selectivity and connectedness.

Question 2: Support, Network Size, and Discord

Model 2 tested whether functional support was related to face selectivity while controlling for the effects of gender and age. Results again indicated no relationship between connectedness and face selectivity ($b = -0.00$, $p = 0.167$). This did not change when focusing in on participants' inner circle instead of their entire network ($b = -0.00$, $p = 0.552$). Next, Model 3 tested whether network size was related to face selectivity. I tested both inner circle size and total network size and found that neither the size of participants' most intimate network ($b = -0.12$, $p = 0.409$) nor the size of their entire network ($b = -0.20$, $p = 0.213$) were related to face selectivity. Finally, discord (Model 4) also was unrelated to face selectivity ($b = 0.18$, $p = 0.599$). This did not change when focusing in on participants' inner circle instead of their entire network ($b = 0.06$,

$p = 0.863$). Thus, to summarize, there was no evidence that either of these social behavior variables was related to face selectivity.

Question 3: Interactions

Finally, Model 5 tested whether any of the three structural variables interacted with connectedness in association with face selectivity. In this model, total (not inner circle) functional support ($b = -0.02$, $p = 0.048$, 95% CI [-0.03, 0.00]) was significantly associated with face selectivity. Thus, for every unit increase in support, face selectivity in performance slightly declined by 0.02 standardized units. Connectedness also marginally interacted with functional support ($p = 0.087$), as displayed in Figure 3. To explore this interaction, I assessed participants at three levels of connectedness (1 SD below the mean, at the mean, and 1 SD above the mean) and evaluated the association between support and face selectivity at these three levels. There was no association between support and face selectivity for individuals who report high levels of connectedness ($b = 0.00$, $p = 1.00$). However, there were negative associations between support and face selectivity for individuals who reported low ($b = -0.01$, $p = 0.03$, 95% CI [-0.01, 0.00]) and mean ($b = -0.00$, $p = 0.09$, 95% CI [-0.01, 0.00]) levels of connectedness. In other words, when people report lower levels of connectedness, low levels of support are related to higher face selectivity in recognition behavior.

No other marginal or significant interactions emerged, including when substituting inner circle support and discord scores instead of total support and discord scores.

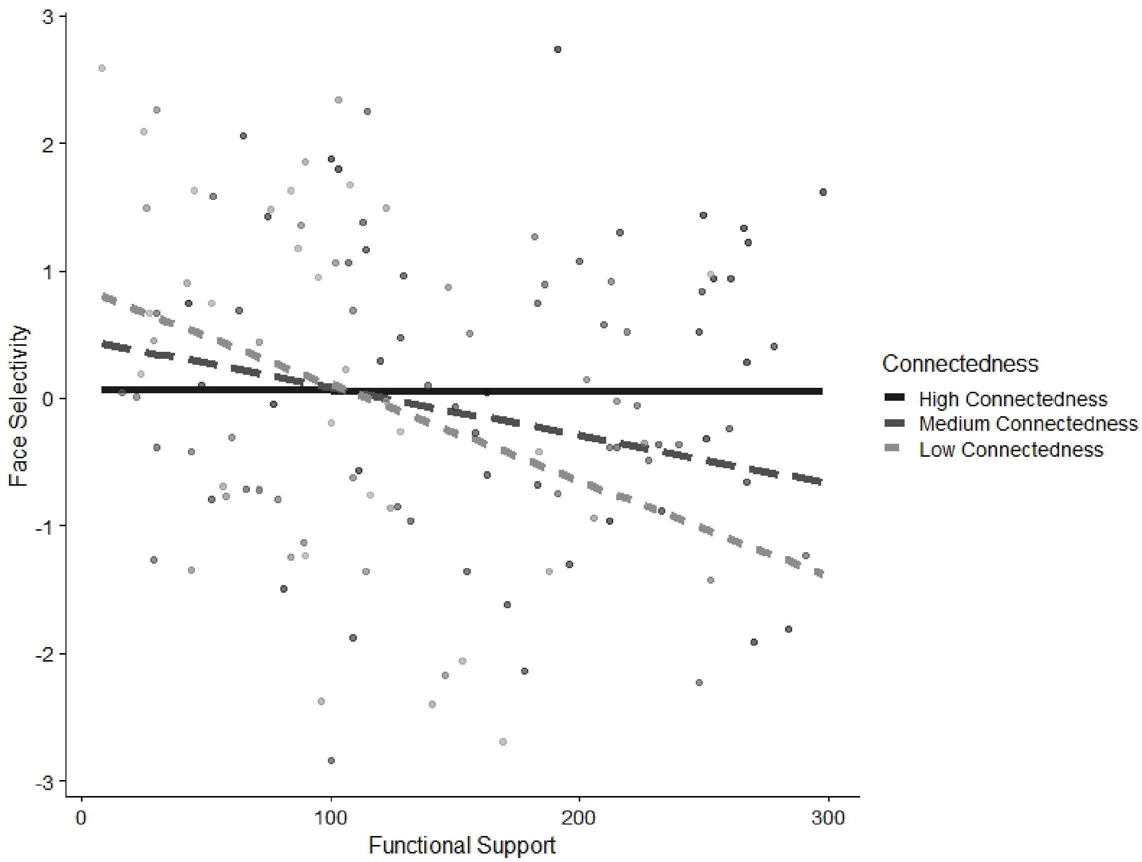

Figure 3: An interaction between connectedness and functional support indicates that support was negatively associated with the difference score at low levels of connectedness. As participants' level of support increased, their recognition tended to favor car recognition over face recognition.

Chapter 3

Discussion

This study sought to uncover the nuances of individual differences in face recognition, including the relevance of social behavior to recognition abilities. Previous research has suggested that face recognition ability is an important aspect of social interaction, as it is related to extraversion, empathy, autism-like traits, social support, and network size, among other variables (Rigby et al., 2018; O'Reilly & de Haan, 2009; Li et al, 2010; Ketay et al., 2019; Germine et al., 2011). However, it is unclear how or why social interaction may contribute to face recognition, particularly with respect to recognition of unfamiliar faces.

At its heart, this issue addresses both within-person and between-person variance in recognition abilities. On one hand, unfamiliar face recognition abilities may facilitate strong relationships with others, indicating a positive association between face recognition and measures of social behavior like social support, as is primarily indicated by clinical literature. This model highlights between-person differences in face recognition abilities, as those who have better recognition ability may have better social outcomes, including social support. This model also places face recognition as a predictor of social behavior. On the other hand, unfamiliar face recognition abilities may be dynamic within persons, serving to build strong relationships, and then dissipating once those relationships have been built. This model, which places face recognition as the dependent variable, addresses within-subject differences in face recognition abilities over time, as indicated by research into belongingness, exclusion, and social well-being in relation to unfamiliar face recognition abilities.

My previous research has highlighted the evidence for between-subjects differences, as has much of the research in this field. I have previously found that face recognition abilities are negatively associated with differences in levels of social support and network size between participants, and positively associated with differences in levels of social discord between participants. To extend this research by incorporating a variable that potentially captures the dynamic nature of face recognition abilities, I designed a study assessing the relationship between face recognition and connectedness. In contrast to other variables, connectedness assesses qualitative measures of a participant's social behavior, rather than how people they are in contact with or how much support they receive. In theory, two individuals could have a large difference in a variable like support, while still experiencing similar levels of connectedness as an index of their feelings about their relationships. As a result, connectedness offers an innovative way to determine how face recognition may serve to satisfy basic human needs in social belonging.

I hypothesized that connectedness would moderate the effects of the structural social behavior variables on face recognition ability. To summarize, if a participant is experiencing high levels of connectedness, then the quantitative components of their social behavior, such as how many people they consider part of their intimate network, for example, will have no relationship with their recognition ability. In essence, their need to belong is satisfied, and as a result, they may not necessarily have a desire to connect with unfamiliar partners. On the other hand, participants experiencing low levels of connectedness have not addressed their need to belong, and thereby will experience motivation to find people who can address this need. This motivation may very well be related to increased face recognition ability, as evidenced by experimental studies involving exclusion and face recognition.

Questions 1 and 2: Limited Evidence

In this project, I sought to determine whether individual differences in certain social behavior characteristics, including social support, social discord, network size, and connectedness, were associated with individual differences in face recognition ability, as operationalized by face selectivity. The data indicate that the association between these variables is limited at best. For Question 1, there was no evidence to suggest that connectedness in of itself is associated with face selectivity. This contrasts with previously described data, which indicate that similar constructs like belonging are related to face processing behavior (Sacco et al., 2011; Gaither et al., 2016; Van Bavel et al., 2012). However, there are three important notes to make in comparing the project described here to this other data. First, many of these studies involved experimental manipulation, rather than observational data collection techniques, such as a survey. For example, several induce threats to belonging or connectedness and examine how the introduction of these threats affect social processing behavior. The null findings from this study serve as a reminder to the differences between experimental methods and observational methods. Second, even among studies that do use surveys or other observational methods, there is great diversity in the measures used. While many studies generally refer to belonging, this is often operationalized as loneliness (for example, Beller and Wagner, 2018; Shevlin et al., 2015). Thus, this project differs from others in the measures employed. Finally, it is crucial to point out that no studies have directly assessed general face recognition ability, using a test as standardized as the CFMT+, in comparison to connectedness. The one previously cited study that tested face recognition used experimental manipulation of belonging and tested recognition among subsets of faces (Van Bavel et al., 2012). While the CFMT+, containing White male faces, does reflect a subset of faces, it is also purported to reflect general face recognition ability (Duchaine & Nakayama, 2006; Russell et al. 2009). If this is true, there is no evidence that connectedness is related to general face recognition ability.

For Question 2, there is also limited evidence that individual differences in the structural social behavior variables are associated with differences in face recognition ability. None of the analyses offered any indication that network size is related to face-specific recognition, in contrast to my previous work. To add, the evidence replicating the effect of discord was also weak. Finally, while the data do offer some support for the idea that social support is related to face-specific recognition, this effect appears weak. Thus, the evidence in favor of Hypothesis 2 is lacking. It is worthwhile noting that even when running models in which face recognition is regressed on each social variable without the other variables (i.e., simple regression while controlling for car recognition, gender, and age), none of the variables are related to face recognition.

These findings may potentially be due to the sample, rather than the effect overall. Of note, the average age of the sample ($M = 24$) is noticeably older than my previous samples ($M \sim$ 19 years). Thus, it is entirely possible that the difference in effects between this study and my previous study is due to differences in the developmental context of each sample. At a younger age, participants may have just begun branching out socially, forming new relationships, and exploring their identities. At a slightly older age, perhaps participants may have made substantial progress in that regard, becoming more accustomed to navigating new social contexts. As evidence, the distribution of social behavior scores appears to differ between samples. For example, in this study, average functional support scores ($M = 139.65$, $SD = 77.77$) are noticeably lower than that of my previous work ($M = 222.03$, $SD = 48.38$). Circle sizes were also smaller in this sample (Circle 1: $M = 5.25$, $SD = 3.97$; Total: $M = 13.71$, $SD = 9.39$) than that of my previous study (Circle 1: $M = 8.86$, $SD = 4.32$; Total: $M = 38.43$, $SD = 15.35$). Each of these differences are statistically significant ($p < 0.001$). While it should be noted that the sample of this project is twice as large as my previous sample assessing network size and social support, these differences suggest that the findings of this study may reflect the different developmental context of this sample.

Question 3: Evidence for an Interaction

Third, for Question 3, there is limited evidence for an interaction between connectedness and any of the structural social behavior variables in association with face selectivity. To be precise, there was only evidence for a marginal interaction between functional support and connectedness in predicting face selectivity. This marginal interaction must be tempered with the understanding that there were no main effects of support or connectedness when examining one of these variables without the other (Model 1, Model 2). Even still, this finding appears to moderately support the Need to Belong model, in that it reveals that individuals low in connectedness exhibit a stronger association with support on their face selectivity relative to individuals high in connectedness. Thus, it is possible that individuals low in connectedness are strongly motivated to supplement their need to belong by finding new connections. However, this finding suggests that high levels of support may plausibly buffer against the effects of low connectedness, while for those with low levels of support, the lack of belonging is particularly salient. Thus, this research indicates that support and connectedness may function alongside each other in a unique way compared to network size and social discord.

Interestingly, the literature indicates that support is often studied alongside other measures of belonging, or the lack thereof, operationalized as loneliness. For example, support has been found to buffer the negative effects of loneliness (Lee & Goldstein, 2016; Brunsting et al., 2019; Freak-Poli et al., 2021). Most recently, researchers have begun pondering how the COVID-19 pandemic, with the effect it had on restricting face-to-face social interaction, may have contributed to a lack of social support and thereby an increase of loneliness (Saltzman et al., 2020). This literature seems to indicate that a lack of support frequently coincides with a lack of belonging and the existence of loneliness. In my study, I found evidence for a positive relationship between support and connectedness; in combination with the findings described here, this suggests that support is important at each extreme of belonging, with a consistently positive relationship.

It is possible that the same cannot be said for the other measures of social behavior I included in this study. For example, it is entirely possible for conflict to occur in close relationships. Indeed, research has focused heavily on how to appropriately navigate conflict in intimate relationships, suggesting that it is a frequently occurring phenomenon within a relationship between close partners (Prager et al., 2015; Fryling & Hayes, 2019; Gesell et al., 2020). As a result, the relationship that exists between support and the strength of an individual's connections does not necessarily exist between conflict and connectedness. In other words, the amount of conflict can vary across levels of connectedness. Similarly, research into social networking sites has indicated that the relationship between network size, along similar measures like frequency of contact, and relational intimacy is not as simple as a simple linear relationship (Roberts & Dunbar, 2011; Lee et al., 2018; Sutcliffe et al., 2018; Pollet et al., 2011). Thus, social support theoretically differs from these other measures in that existing research indicates it is perhaps the closest of these in parallel to social belonging and connectedness. Therefore, it is possible that the interaction between only support and connectedness, as opposed to support and the other variables, explains these findings.

This raises the question of whether support can be considered distinct from connectedness. The literature seems to indicate that while distinct from each other, support and connectedness appear to feed into each other, and both serve as important components of mental and emotional well-being (Williams & Galliher, 2006; Pryce et al., 2019; Matlin et al., 2011). In my own research, I found that support was mostly strongly correlated with connectedness compared to the other measures of social behavior (Table 2). Thus, this seems to suggest that support shares considerable overlap with connectedness. Future analyses with this dataset might reveal the nature of this overlap, including the degree to which support and connectedness either overlap or differ in assessing social wellbeing.

As a final point in this discussion, it should be noted that the scoring method is not uniform across each of the social behavior variables. Support is summed across items and nominees, connectedness is summed across items, and discord is averaged across items. Thus, these variables are not necessarily operationalized uniformly across their measures. However, these approaches reflect subtle nuances regarding what it means to experience social support, discord, and connectedness in the real world. Social support, for example, as measured by the

Norbeck questionnaire, taps into the degree to which participants have support resources available to them. By contrast, discord as measured by the Network of Relationships Inventory refers to how frequently participants experience conflict in their networks. Finally, connectedness assesses the degree to which participants' need to belong has been addressed in various ways. Thus, while these variables are measured and scored in different ways, each of them measures social behavior in a specific way.

In addition, the way each of these variables was scored may have influenced the findings from this project. For example, averaging connectedness and support would drastically decrease the range of these variables; with a smaller range, it is possible that it would be more difficult to assess individual differences. In other words, the findings may not have indicated an interaction between connectedness and support in association with face selectivity. Thus, future analyses with these data might focus on how different approaches to scoring might influence the findings of the project.

Differences between Face and Object Recognition

In this study, I used a difference score between face recognition and object recognition as the dependent variable. This contrasts with my previous research, in which I have treated face recognition proper as the dependent variable and treated car recognition as a control variable. Using this approach, the results slightly differed than what might be expected from my previous studies, namely in a lack of main effects of social support, network size, and social discord. This begs the question – what distinguishes this difference score from raw face recognition scores?

There are a few existing studies that have used a difference score to compare face and object recognition. Ruosi Wang and colleagues (2012) used a difference score to compare performance on a face old-new recognition task and a flower old-new recognition task and found that the difference score distribution better reflected a normal distribution. The authors argued that the difference-based score more appropriately targeted face recognition ability specifically, rather than reflecting general processing ability. Another study applied a similar approach while using the two Cambridge tasks, although they used the original version of the CFMT using 72 items (Gerlach and Starrfelt, 2018). Citing the controversy surrounding the use of a difference score (DeGutis et al., 2013), the authors used both a difference-score approach and a regression-based approach, where the CCMT was included in a regression as a control predictor. Interestingly, they only observed a significant relationship with their dependent variable when using the difference score, as opposed to using the regression approach. However, the data did indicate a similar trend when using the regression approach, despite a lack of significance. The authors hypothesize that the significance of the difference approach is potentially due to shared variance between the two recognition tasks being removed by creating the difference score. Still, critics of the difference-score approach point out that under the difference approach, variance differences between the two tasks are conflated (DeGutis et al., 2013). Thus, it is crucial to caution any interpretation of these results with the knowledge that difference scores may not completely reflect population-level variance in face recognition ability.

With this caveat established, while it was not a primary focus of this study to compare a regression approach to a difference score approach, I also ran the same analyses I have described here using a regression approach rather than a difference score approach, just as Gerlach and Starrfelt did (2018). Using this approach, the interaction between support and connectedness in association with face recognition was also marginal ($b = 0.00$, $p = 0.097$, 95% CI [0.00, 0.00]), and simple slope analysis revealed there was no effect of support at either of the three levels of connectedness ($p > 0.11$). However, the slopes at low connectedness ($b = -0.06$, $p = 0.11$) and medium connectedness ($b = -0.02$, $p = 0.34$) trended in the same direction as they did when using face selectivity as the dependent variable. Thus, across the mix of results from the three studies I have led during my time in graduate school, findings indicate that individual differences in social behavior are related to differences in social information processing. In other words, the use of a different dependent variable in this study adds to the conclusions of my previous work.

Developmental Context

It is also important to place these results in the appropriate developmental context. The participants in this study were included both emerging adults, ranging from 18 to 25, and slightly older young adults, ranging from 26 to 28. Emerging adults are beginning to establish their independence from their parents, exploring their social context, including in the college environment, and forming meaningful relationships and partnerships with others. The data from this study may reflect the degree to which emerging adults have successfully reached these developmental goals. High levels of connectedness and support may reflect success in finding belonging with others; on the other hand, low connectedness and support may reflect further need to achieve these goals, resulting in a desire to meet and become acquainted with new potential relationship partners (Lee et al., 2001). In the case of low connectedness, face recognition may aid in this endeavor of forming new relationships.

However, as previously discussed, the literature surrounding the social behavior of emerging adults may have only limited applicability for the data described in this study. The non-emerging adult participants in this study may have been able to create more intimate social networks, established important social ties, and identified important and significant life partners (Erikson & Erikson, 1998). As a result, it is possible that as age increases in emerging and young adulthood, participants' social networks might also change. As such, the motivation to find connectedness and belonging may differ across age in this sample.

Even still, there was limited evidence that the age range of participants in this sample drastically altered the findings of this project with respect to the need to belong. Despite the possibility that the need to belong may manifest differently for participants at the older end of the age range of this sample, this does not mean that this motivation would be non-existent. Indeed, the need to belong is argued to be one of the strongest motivators across the human developmental lifespan (Maslow, 1943; Deci & Ryan, 2000; Maarten et al., 2020). To add, even though emerging adulthood as a developmental range is often restricted to 18 to 25, it is possible if not likely that there is significant overlap with the few years following this range. For example, Erikson's model appears to group emerging adults and young adults together (Erikson & Erikson, 1998). Original conceptualizations of emerging adulthood appear to refer to social development and the occurrence of social milestones, such as marriage, rather than chronological age (Arnett & Taber, 1994). As evidence in this study, between-participant variability in age was unrelated to face recognition, face selectivity, or any of the social behavior variables in this sample. Specifically, age was related to neither connectedness as a measure of belonging, nor the structural variables of size, support, or discord. While these variables do not assess trait-level differences in the need to belong, they do offer some indication towards the degree to which a participant's need has been addressed. Thus, a lack of differences in these variables across age indicates that participants are addressing their need to belong in similar ways, regardless of age. To conclude, while there may be variability in the strength of the need to belong across this sample, the principle of finding belonging remains strong across age.

Finally, in assessing the participants' context in this study, it must also be noted that participants in this study were recruited online, from across the United States. My previous studies primarily recruited college students and emerging adults surrounding Pennsylvania State University. As such, 56% of the participants in this study were White, while 71% of participants in my previous study. While I have not thoroughly examined the other demographic variables, including socio-economic background and educational attainment, it is entirely possible that participants may have varied on several factors across this research. Thus, while this may potentially restrict generalizability across the studies, this current project also extends my previous research by recruiting a more diverse sample. Even still, this aspect of the participants' background must also be considered.

Limitations

One potential limitation of this study is the method of data collection. While using M-Turk may make it easier to recruit more participants, it does not account for the quality of the data. In my previous studies, researchers watched the participants while completing the study to ensure that they were paying attention; however, as this study took place online, I was not able to monitor participants' attention. Thus, it is possible that participants did not pay as close attention as usual, thereby affecting their data, particularly their performance in the recognition tasks.

Another limitation of this study is the nature of the Cambridge task. As previously noted, this version was coded in Psychopy, and is thereby theoretically different than the standard version, even though great care was taken to ensure similarity between this version and the original. In addition, many of the theories driving the hypotheses of this study revolve around distinctions between in-group face recognition and out-group recognition. However, due to available resources and ensuring the feasibility of this project, I have restricted the recognition tasks to include only White faces. Further, despite my previous research indicating strong overlap between the M-CFMT+ and the F-CFMT+, my current proposal is restricted to male faces due to the expected time-course of the protocol, potentially limiting the scope of the conclusions. As a result, a potentially important factor in these analyses, distinguishing between recognition by group of faces, is missing from this project. Still, the Cambridge task have been identified throughout face processing science as standard measures of face recognition abilities. While it would be wise for future research to control for different sets of faces in a similar study, the potential results of this proposed research provide a launching pad to understand these ideas by using a conventional measure.

In addition, my hypotheses revolved around the idea that deficits in unfamiliar face recognition coincide with a procedural focus on a subset of faces that are important to the participant. This would presumably be tested by a test of familiar face recognition. However, I have no such test designated in my proposed research. As a result, it may not necessarily be true that every participant who is a poor recognizer is proficient among a subset of faces. Future research should highlight this by taking care to account for both familiar and unfamiliar face recognition.

Similarly, this study could also be bolstered by taking a longitudinal approach. If my hypotheses are correct, then face recognition abilities are not necessarily stable. That is, in cases of high connectedness, face recognition is worse, while in cases of low connectedness, recognition is better. As a result, it would be worthwhile to take a developmental approach with a similar sample. For example, this research could include a sample of emerging adults across their years at university. The measures would include the same assessments, but the data would be collected at repeated time points. This would reveal how connectedness changes across development, and whether face recognition changes in the same pattern as connectedness. Thus, future studies would be wise to investigate further into the notion of face recognition abilities.

Future Directions

One possible potential implication from this study is that this dataset could be used to advance the scientific study of social constructs like ethnicity and race. I have previously discussed how the face recognition system is hypothesized to be a valuable part of social interaction. Prominent research in this field has highlighted what this means for people from different ethnic-racial groups. For example, as previously discussed, research associating face recognition and belonging have highlighted that those low in belonging are likely to seek out people from their own social group (Van Bavel et al., 2012). This finding reflects the notion of an own-race bias, by which individuals exhibit better ability processing faces from those within one's own ethnic-racial group (Ferguson et al., 2001; Hugenberg et al., 2010; Hugenberg et al., 2013). Notably, the own-race bias suggests that individuals are attuned to process and recognize faces that are deemed socially relevant more efficiently. Similar research has built on the finding with that face recognition is also used to identify potential threats in one's social environment (Berdica et al., 2018; Burra & Kerzel, 2019; Becker & Detweiler-Bedell, 2009; Shasteen et al., 2015). In keeping with the own-race bias, ethnic-racial out-group faces are often deemed threatening (Glasgow et al., 2020; Al-Janabi et al., 2012; Dunham, 2011; Hugenberg & Bodenhausen, 2003; Hugenberg & Bodenhausen, 2004; Halberstadt et al., 2018; Hutchings, & Haddock, 2008).

Most notable for my proposed research, many of the findings in this literature indicate that both quantitative and qualitative experiences with members of different ethnic-racial groups can offset the own-race bias (Valentine, 1991; Valentine et al., 2016; Walker & Hewstone, 2006; Tanaka et al., 2013). Given that I will record the ethnic-racial composition of participants' networks, in addition to both quantitative and qualitative assessments of their relationships, this opens the door for future research to investigate how relationships with members of different ethnic-racial groups relate to face recognition. For example, might my hypotheses as previously espoused differ by participant network composition? Is recognition of White faces associated with the relationships that participants have with their White network partners? Are those who feel more connected because of their relationship likely to have primarily in-group contacts in their inner circle? Is the four-way interaction between gender, connectedness, task, and support specific to White men's recognition of White male faces? In summary, this data will be invaluable to advancing research beyond what is described in this proposal.

Finally, it is worth mentioning that this study took place during the COVID-19 pandemic in the United States. During the pandemic, many relationships consisted primarily of online interaction, rather than in-person contact. While not a focus of this proposed study, the data may allow for a comparison of relationships before the pandemic, based on my previous work, and relationships during and after the pandemic. I asked participants about how their relationships may have changed quantitatively or qualitatively over the course of the pandemic, and several participants indicated some degree of change. Given the novelty of this pandemic, it is difficult to hypothesize what the findings of this study might reflect. Participants did indicate that the pandemic had some impact, as 11% indicated quantitative changes in their network and 41% indicated qualitative changes. The fact that participants underwent such noticeable transformations tied to the pandemic may have very well influenced their levels of connectedness, as well as their support or conflict. While not a primary focus of this current project, this research will at the very least contribute to conversations about the social consequences of the COVID-19 pandemic.

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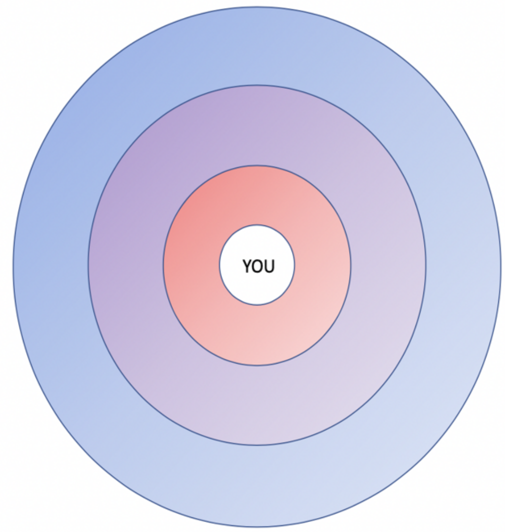
Appendix A: Circles Measure Design

- In the innermost (red) circle, put the initials of anyone in your life who you feel so close to that it is hard to imagine life without them.
- For the middle (purple) circle, write the initials of anyone in your life who you may not feel quite that close to but who is still very important to you.
- For the outside (blue) circle, write the initials of anyone in your life who is close and important enough in your life that they should be placed in your personal network.



Antonucci and Akiyama, 1987

Appendix B: Support Questionnaire

Table 1. Questions for Rating[1] Network Members on the NSSQ

Affect 1: Loved	1. How much does this person make you feel liked or loved? [affect]	Emotional	Functional
Affect 2: Respected	2. How much does this person make you feel respected or admired? [affect]	Emotional	Functional
Affirmation 1: Confiding	3. How much can you confide in this person? [affirmation]	Emotional	Functional
Affirmation 2: Agreeing	4. How much does this person agree with or support your actions or thoughts? [affirmation]	Emotional	Functional
Aid 1: Short term aid	5. If you needed to borrow $10, a ride to the doctor, or some other immediate help, how much could this person usually help? [aid—short term]	Aid	Functional
Aid 2: Long term aid	6. If you were confined to bed for several weeks, how much could this person help you? [aid—long term]	Aid	Functional
Duration	7. How long have you known this person? [duration of the relationship]		
Frequency	8. How frequently do you usually have contact with this person? (phone calls, visits, or letters) [frequency of contact]		

Norbeck, Lindsey, and Carrieri, 1981

Appendix C: Conflict and Antagonism Questionnaire

- Conflict
  - How much do you and this person get upset with or mad at each other?
  - How much do you and this person disagree and quarrel?
  - How much do you and this person argue with each other?
- Antagonism
  - How much do you and this person get on each other's nerves?
  - How much do you and this person get annoyed with each other's behavior?
  - How much do you and this person hassle or nag one another?

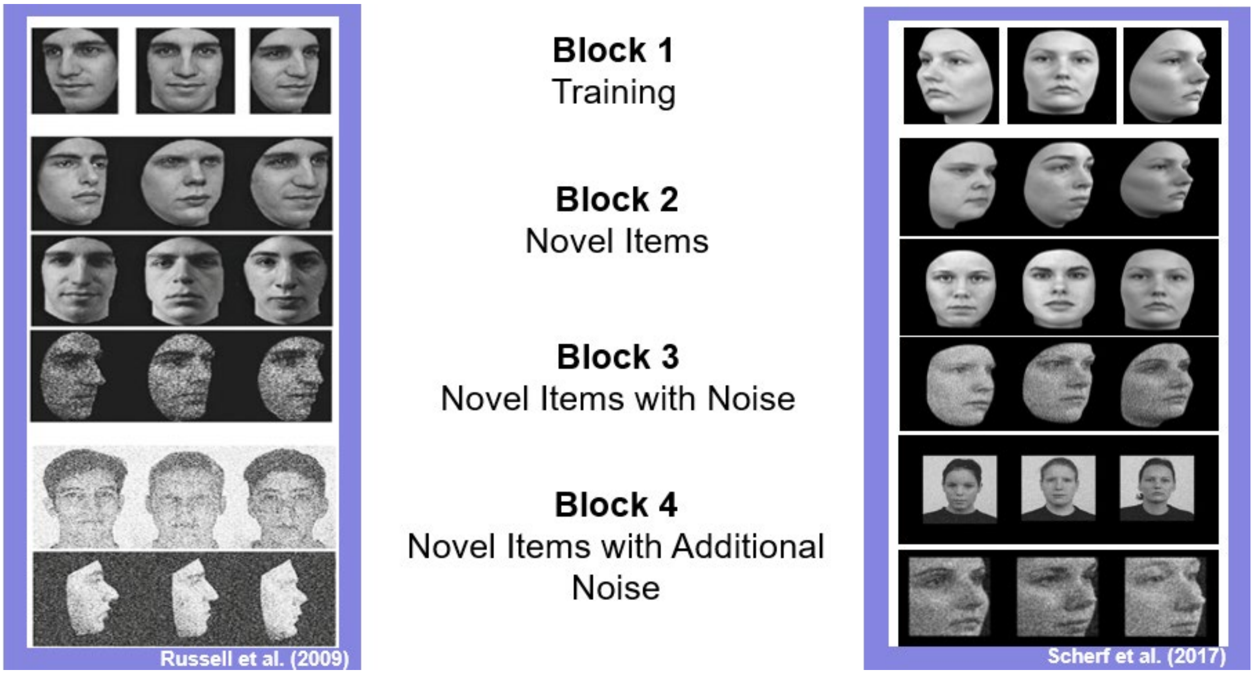
Appendix D: Connectedness Questionnaire

Social Connectedness Scale – Revised

Item
1. I feel distant from people.
2. I don't feel related to most people.
3. I feel like an outsider.
4. I see myself as a loner.
5. I feel disconnected from the world around me.
6. I don't feel I participate with anyone or any group.
7. I feel close to people.
8. Even around people I know, I don't feel that I really belong.
9. I am able to relate to my peers.
10. I catch myself losing a sense of connectedness with society.
11. I am able to connect with other people.
12. I feel understood by the people I know.
13. I see people as friendly and approachable.
14. I fit in well in new situations.
15. I have little sense of togetherness with my peers.
16. My friends feel like family.
17. I find myself actively involved in people's lives.
18. Even among my friends, there is no sense of brother/sisterhood.
19. I am in tune with the world.
20. I feel comfortable in the presence of strangers.

(Lee, Draper, & Lee, 2001)

Appendix E: Face Recognition Task



Appendix F: Variable Glossary

Variable	Measure	Description
Connectedness	SCS-R	The degree to which the participant feels belonging in their life.
Discord	NRI	The degree to which participants experience conflict and antagonism in specific relationships in their life. Can distinguish between Circle 1 relationships and relationships across circles.
Support	Norbeck Questionnaire	The degree to which participants experience social support in specific relationships in their life. Can distinguish between Circle 1 relationships and relationships across circles.
Total Network Size	Circles Measure	How many people participants list in their social network.
Circle 1 Network Size	Circles Measure	How many people participants list in their most intimate social network.
Face Recognition	M-CFMT+	Participants' ability to recognize unfamiliar faces among distractors.
Structural Variables	NRI, Norbeck, Circles	Includes Discord, Support, and Network Size, which all assess structural components of participants' networks, in contrast to connectedness.
Car Recognition	CCMT	Participants' ability to recognize unfamiliar cars among distractors.
Recognition Difference	M-CFMT+, CCMT	The difference in recognition ability between car recognition and face recognition.

Appendix G: Models

Question 1

Model 1:

Alternative: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \beta_{3j} * (Connectedness_j) + \varepsilon_j$

Null: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \varepsilon_j$

Question 2

Model 2:

Alternative: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \beta_{3j} * (Support_j) + \varepsilon_j$

Null: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \varepsilon_j$

Model 3:

Alternative: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \beta_{3j} * (Network\_Size_j) + \varepsilon_j$

Null: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \varepsilon_j$

Model 4:

Alternative: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \beta_{3j} * (Discord_j) + \varepsilon_j$

Null: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \varepsilon_j$

Question 3

Model 5:

Alternative: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \beta_{3j} * (Network\_Size_j) + \beta_{4j} * (Support_j) + \beta_{5j} * (Discord_j) + \beta_{6j} * (Connectedness_j) + \beta_{7j} * (Network\_Size_j) * (Connectedness_j) + \beta_{8j} * (Support_j) * (Connectedness_j) + \beta_{9j} * (Discord_j) * (Connectedness_j) + \varepsilon_j$

Null: $Face\_Selectivity_j = \beta_{0j} + \beta_{1j} * (Gender_j) + \beta_{2j} * (Age_j) + \varepsilon_j$