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Understanding Differences in Social Learning

Joshua Patenaude, *The University of Western Ontario*

Supervisor: Heerey, Erin, *The University of Western Ontario*

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Abstract

Previous research has shown that individuals with autism spectrum disorder (ASD) appear to learn from social and non-social rewards at different rates compared to typically developing individuals. Several hypotheses have been developed to explain these differences, including the social motivation hypothesis, the weak central coherence hypothesis and hypotheses related to probabilistic learning ability. However, in all cases, the literature shows only mixed support for these ideas. This dissertation focuses on identifying which assumptions from these hypotheses replicate and what replication successes and failures mean for the study of autism-spectrum traits within the general population.

This work takes a "spectrum" approach to autism that assumes ASD-related traits occur on a scale continuum. It therefore is designed to test the central predictions of each of these hypotheses amongst participants sampled from the general population. The use of general population samples confers the considerable advantage of allowing adequate statistical power for hypothesis tests. In addition to these hypotheses, this dissertation explores how social behavior and interaction outcomes relate to ASD-traits and task outcomes.

Interestingly, results ran contrary to many of the previous findings in the literature. Despite evidence of associations within the general population and ASD-traits, I failed to find clear associations between ASD-traits and predictions made by the Social Motivation Hypothesis, the Weak Central Coherence Hypothesis or hypotheses related to probabilistic learning ability. Despite these results, data on real social behavior and social outcomes did vary as a function of ASD-relevant traits. Specifically, the interaction partners of individuals who reported higher levels of ASD-traits experienced them as less likable and reported worse interaction quality. Additionally, individuals reporting higher levels of ASD-related traits were less expressive than those reporting fewer traits.

Overall, while predictions about ASD-traits and cognitive/motivational processes did not appear to replicate within the general population, ASD-traits do appear to be related to real-life social behavior and interaction outcomes associated. Together, these findings document subtle social behavior differences associated with ASD traits in the absence of social cognitive differences and suggest that major theories of autism may not sufficiently explain the causes of altered social behavior in those with autism-spectrum conditions.

Keywords

Autism, Weak Central Coherence, Social Motivation, Probabilistic Learning, Social Interactions

Summary for Lay Audience

Autism spectrum disorder is a pervasive developmental disorder that deeply impacts the social lives of those diagnosed. Across the years, many hypotheses have been developed to explain how this disorder disrupts social function. This dissertation explores key predictions made by three major theories of autism: the social motivation hypothesis, the weak central coherence hypothesis and probabilistic learning hypotheses. Because research over the last decade suggests that autism traits occur on a spectrum, rather than representing a qualitative shift in function or symptoms with the presence of diagnosis, the samples in this set of studies come from the general population.

This work examines three major research questions: 1) Do autism-spectrum traits affect how people value smiles? 2) Do autism-spectrum traits affect how you perceive the world? 3) Do autism-spectrum traits affect how people learn from ambiguous environments and feedback? In addition to these questions, this dissertation also explores how social behavior and social interaction outcomes relate to autism-spectrum traits.

Interestingly, the present results were generally contrary to the predictions made by major theories. Indeed, most of the findings showed little if any effect. Additionally, the tasks in these studies, which have been theorized to underpin social function showed no clear relationship to social interaction outcomes, suggesting that social interaction skill is not related to autism traits in nearly as straightforward a fashion as previous work has claimed. Nonetheless, findings did show a clear relationship between autism-spectrum traits and social interaction outcomes, as well as social behavior. More specifically, the more autism-spectrum traits an individual endorsed, the less their social interaction partner liked them and the more awkward their partner felt the interaction was. Lastly, autism-spectrum traits were found to be associated with key social behaviors including smiling and eye-gaze, such that those endorsing more autism-spectrum traits smiled less and gazed downward substantially more than did those endorsing fewer traits.

Overall, while the major hypotheses of autism-spectrum disorder seem to fall short in their ability to explain the disorder, this dissertation upholds a clear link between autism spectrum traits and naturalistic social behavior and social outcomes.

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Introduction

Autism spectrum disorder (ASD) is a pervasive developmental disorder that affects millions of people around the world (Hansen, Schendel, & Parner, 2015). The American Psychological Association (APA) defines ASD as the presence of persistent impairments in reciprocal social communication and social interactions, as well as restricted repetitive patterns of behavior, interests, or activities. These symptoms are present from early childhood and limit or impair everyday functioning. Manifestations of the disorder also vary greatly depending on the severity of the condition, developmental level, and chronological age, hence the term spectrum. (American Psychological Association, 2013). More specifically, the literature characterizes ASD based on symptoms including prominent social interaction difficulties, behavior problems, difficulties in generalizing from exemplars to prototypes and communication deficits (Fountain, Winter & Bearman, 2012; Landa, Holman & Garrett-Mayer, 2007; Montes & Halterman, 2006). For example, people diagnosed with ASD may experience difficulty recognizing and interpreting nonverbal cues (e.g., gestures, prosodic cues and facial expressions), use language atypically, produce inappropriate emotional responses and may appear to lack empathy for others (Baron-Cohen & Wheelwright, 2004; Matson, Kozlowski, Hattier, Horovitz & Sipes, 2012). ASD typically manifests early in childhood, leading to atypical developmental trajectories in both cognitive and behavioral domains (Anderson, Maye & Lord, 2011; Fountain, et al., 2012).

In the social domain, the atypical behavior patterns many people with ASD display may contribute to difficulties in the formation and maintenance of social relationships (Jobe & White, 2007). In the cognitive domain, even when intellectual disabilities are absent (e.g., “high functioning” autism), individuals with ASD often experience difficulty with the acquisition and understanding of abstract concepts, difficulties adapting to and learning from unpredictable environments and “executive function” deficits (Baron-Cohen & Wheelwright, 2004; Ozonoff, Pennington & Rogers, 1991). Together, these difficulties create a social learning and interaction history that differs substantially from the experiences that characterize “typical” development and often results in delayed academic and social achievement (Jobe & White, 2007).

These developmental differences often greatly influence an individual’s quality of life, and while there are no known cures for ASD, studies have found that early intervention and intensive treatment can improve cognitive ability, reduce inappropriate behaviors, and enhance longer-term functioning (Dawson & Burner 2011). For example, research has shown that simple operant learning strategies, such as reinforcement learning, can improve social behavioral outcomes (Matson, Matson & Rivet, 2007) and social interaction quality (Hastings, 2003) in children with ASD. These learning strategies form the foundation of a primary behavioral intervention in autism, Applied Behavioral Analysis (ABA). ABA-based treatments use reinforcement-learning strategies to reduce challenging behaviors and increase prosocial behaviors (Matson et al., 2012). ABA-styled treatments delivered early in childhood show medium to large effect sizes compared to control treatments when examining behavioral outcomes (Hastings, 2003; Matson et al., 2012). However, outcomes vary greatly, with some individuals/groups showing little improvement (Sallows & Graupner, 2005). Even though results from treatment are not totally consistent, this work generally shows that reliable administration of behavioral reinforcement likely enhances outcomes (Matson et al., 2012; Peters-

Scheffer, Didden, Korzilius & Sturmey, 2011). This suggests that some aspects of reinforcement learning are conserved within ASD.

Despite the fact that consistently applied reinforcement in the context of ABA treatments appears to be effective for at least some individuals with ASD, several studies in experimental settings have shown reinforcement-learning model failures in areas including visual learning (Harris et al., 2015; Scherf et al., 2018), social versus non-social rewards (Lin, Adolphs & Rangel, 2012; Scott Van Zeeland et al., 2010), and probabilistic learning (Robic et al., 2015; Solomon et al., 2015; Solomon, Smith, Frank, Ly & Carter, 2011). Because the success of ABA treatments appears to relate to consistency in the application of reinforcements and many of the reinforcement-learning failures documented in the experimental literature occur in the context of probabilistic reinforcement, this suggests that atypical learning mechanisms may feature in ASD symptomatology. In particular, the social difficulties associated with ASD may stem from difficulties learning from probabilistic reinforcement. For example, associative learning may play a role in social learning. Evidence suggests that associative learning ability at one-month predicts social engagement at 5, 9, and 12 months (Reeb-Sutherland, Levitt & Fox, 2012). If these ideas are correct, atypical learning may by a central cause of the social behavioral differences in ASD. With these considerations in mind, this dissertation will focus on three central hypotheses that aim to explain the social deficits of ASD: the social motivation hypothesis; the weak central coherence hypothesis; and probabilistic hypotheses of learning and decision-making. I review each of these theories below.

1.1 The Social Motivation Hypothesis of Autism

The social motivation hypothesis (SMH) of autism, states that individuals with ASD experience early deficits in social motivation, which reduces their ability to attend to, and learn from social information in their environment (Bottini, 2018; Chevallier, Kohls, Troiani, Brodkin & Schultz, 2012). The lack of basic social learning results in reduced understanding of social versus non-social stimuli and this further impairs social skill and cognitive development. The downstream effects caused by alterations in developmental trajectory are thought to lead to impaired socio-cognitive development in domains such as theory of mind (ToM; Burnside, Wright & Poulin-Dubois, 2017), which in turn leads to atypical social behaviors and responses (Chevallier, et al., 2012; Kohls, Chevallier & Schultz, 2012; Dawson, Meltzoff, Osterling, Rinaldi & Brown, 1998; Miligan et al., 2007; Rozga et al., 2011; Scheeren, de Rosnay, Koot & Begeer, 2013; Senju et al., 2012; Wellman et al., 2004). Moreover, proponents of this theory suggest that individual differences in the motivation for social rewards may play a role in shaping social responding across the full spectrum of the general population (Burnside et al., 2017; Chevallier, et al., 2012). Therefore, this theory formulates social motivation, and downstream effects on social ability, as an individual difference that is applicable regardless of the presence of any formal diagnosis. According to this idea, any differences in early motivation for social contact should result in altered social learning opportunities and, across time, result in measurable differences in social cognition, including ToM (Bottini, 2018; Chevallier, et al., 2012; Estes et al., 2015; Scott Van Zeeland et al., 2010).

One of the biggest strengths of this theory is its ability to explain the social deficits of ASD. Proponents of the social motivation hypothesis suggest that social motivation provides the guidance for human social behavior and that it is the disruption of people's social motivation that underpins the social deficits seen in ASD (Bottini, 2018; Burnside et al., 2017; Chevallier, et al., 2012). More specifically, proponents of the theory suggest the capacity for social motivation explains individual differences in social behaviors including social orientation, seeking and liking behaviors, social maintenance, and smiling engagement (Bottini, 2018; Bowles, 2008; Chevallier, et al., 2012; Elsabbagh et al., 2013; Leary & Allen, 2011). When severe deficits in social motivation occur, ASD often result (Chevallier, et al., 2012; Choi et al., 2015; Dawson & Munson, 2002; Hobson & Lee, 1998; Riby & Hancock, 2008; Samson, 2013; Scott Van Zeeland et al., 2010; Supekar et al., 2013).

Social orientation, the degree to which people attend to social stimuli, is one critical domain of social behavior that the social motivation hypothesis may explain. For example, the ability to experience social information as rewarding may predict the tendency to orient toward sources of social information. Social motivation may drive people's desire to engage in social orienting behaviors and may be present as early as infancy, driving infants' preferences to attend to face-like stimuli (Elsabbagh et al., 2013; Gliga, Elsabbagh, Andravizou & Johnson, 2009). Additionally, another important aspect of social orientation is social gaze. For example, social gaze behavior, including direct gaze, both attracts attention and has been found to improve identification of relevant social cues such as a partner's emotions and gender (Macrae, Hood, Milne, Rowe & Mason, 2002; Senju & Johnson, 2009; Vernetti et al., 2018).

Proponents of the social motivation hypothesis have claimed that if individuals with ASD have reduced social motivation they should engage in fewer social orientation behaviors (Chevallier, et al., 2012). This prediction is supported by findings in the literature suggesting that individuals with ASD show decreased eye contact, impairments in orienting to social stimuli and reduced gaze fixations on faces, especially in the eye region, compared to control groups (Galli et al., 2019; Klin, Jones, Schultz, Volkmar & Cohen, 2002; Osterling, Dawson & Munson, 2002; Riby & Hancock, 2008). These findings all indicate reduced social orienting (Chevallier, et al., 2012; Clements et al., 2018).

In contrast to individuals with ASD, who show limited engagement in social orientation behaviors, individuals in the general population, seek out and engage in social behavior, such as social orienting behavior, frequently (Von Cranach, 1971). In fact, evidence suggests that people exert high levels of effort for a chance to engage in social interactions or access social rewards (Hayden, Parikh, Deaner & Platt, 2007; Tamir & Hughes, 2018; Tamir, Zaki & Mitchell, 2015). Supporting this idea, evidence also shows that people enjoy social interactions with both friends and strangers, especially when they involve the chance to cooperate and offer mutually satisfying outcomes (Fehr & Camerer, 2007; Kawamichi et al., 2016; Tamir et al., 2015). One reason that social interactions may be so enjoyable is that social rewards such as smiles, agreement, trustworthy behavior, behavioral mimicry, etc., have been found to have intrinsic motivational value (Decety, Jackson, Sommerville, Chaminade & Meltzoff, 2004; Declerck, Boone & Emonds, 2013; Shore & Heerey, 2013; Tabibnia & Lieberman, 2007; Tamir et al., 2015).

Proponents also argued that people have an intrinsic motivation to engage in social behaviors. On average, studies have found that the exchange of social cues is intrinsically rewarding, whether it be engaging in general social activities such as talking with a group of friends, or engaging in pro-social behavior like helping others (Carr & Walton, 2014; Chatzisarantis, Hagger, Smith & Sage, 2006; Chevallier, et al., 2012; Jaques et al., 2018; Kamalan, 2019). If this is the case, then individuals who lack social motivation should engage in fewer social or pro-social behaviors and put less effort into seeking out social rewards by behaving socially/pro-socially. Study findings supporting this idea show that individuals with ASD put less effort into engaging in collaborative activities, are less likely to seek out social rewards such as praise, initiate social interactions less frequently, and engage in fewer social engagement behaviors such as declarative pointing (Demurie, Roeyers, Baeyens & Sonuga-Barke, 2011; Mundy, 2019; Mundy, Sullivan & Mastergeorge, 2009; Sepeta,Tsuchiya, Davies, Sigman, Bookheimer & Dapretto, 2012; Vulchanova, Ramos Cabo & Vulchanov, 2019).

As one might predict from these results, many individuals with ASD also report having fewer friends than their more socially motivated peers (Howlin, Goode, Hutton & Rutter, 2004; Sedgewick, Hill, Yates, Pickering & Pellicano, 2016; Taheri, Perry & Minnes, 2016). Interestingly, despite having fewer friends, they report little to no increase in loneliness (Chamberlain, Kasari & Rotheram-Fuller, 2007). This finding is consistent with the idea that social motivation is an important and intrinsic driver of the desire to form social connection by seeking social closeness with others.

Researchers have also used the social motivation hypothesis framework to suggest that social maintenance behaviors, actions that elicit positive feelings in others, constitute displays of social motivation. According to this idea, social motivation drives an individual's 'want' to engage in social interactions over a prolonged period (Chevallier, et al., 2012; Leary & Allen, 2011). Supportive maintenance behaviors, including praise and flattery, help individuals connect with both social groups and other individuals by eliciting positive attitudes in receivers (Stafford & Canary, 1991). People who report higher levels of social motivation, also engage in social maintenance behaviors more often than do those reporting lower social motivation levels (Cialdini & Goldstein, 2004; Lakin & Chartrand, 2003, Molden, Lucas, Gardner, Dean & Knowles, 2009). Conversely, individuals with ASD engage in fewer social maintenance behaviors such as flattery, greeting behavior, and humor (Chevallier, Molesworth & Happe, 2012; Hobson & Lee, 1998; Samson, 2013).

Finally, proponents of the social motivation hypothesis suggest that individuals with ASD have deficits in representing the reward value of social stimuli and that this should lead to deficits in social reward processing (Bottini, 2018; Chevallier et al., 2012), which ultimately reduces the utility of social rewards such as eye-contact and smiles. A recent meta-analysis has found general support for this idea, though it also noted inconsistencies in some findings that appeared to relate to methodological differences (Bottini 2018). Specifically, studies that examined reward learning based on social rewards, defined as tasks that require participants to learn contingencies from social feedback (e.g., Choi et al., 2015; Scott Van Zeeland et al., 2010), found consistent support for the social motivation hypothesis. In contrast, studies that examined explicit reward valuation, defined as tasks in which participants rated their liking of the stimuli/rewards they saw (e.g., Benning et al., 2016; Ewing, Pellicano & Rhodes, 2013;

Gilbertson, Lutfi & Weismer, 2017), did not appear to support the social motivation hypothesis. That is, studies in which participants self-report their liking for social stimuli tend not to find ASD-related differences whereas those that examine learning from social rewards do appear to find such differences. Arguably, however, learning from social rewards requires attention to those rewards, positive valuation of those rewards, the ability to learn environmental contingencies, and memory for outcomes, etc. Thus, current research findings provide mixed support for the social motivation hypothesis, suggesting that further testing is needed to clarify whether individuals across the autism spectrum show differences in how they value social rewards.

Importantly, there are several serious critiques against the social motivation hypothesis. Many of the critiques of this hypothesis suggest that deficits in social motivation may be far less common than typically reported (Livingston, Shah & Happé, 2019), such that some individuals with ASD show no deficits in social motivation (Bottini, 2018; Garman et al., 2013; Livingston, Shah & Happé, 2019). Critiques also suggest that many of the ‘social deficits’ seen in individuals who experience high levels of ASD-related traits and individuals with ASD, have simpler, more straightforward explanations (Jaswal & Akhtar, 2019; Kapp, Goldknopf, Brooks, Kofner & Hossain, 2019; Uljarević, Vivanti, Leekam & Hardan, 2019). Indeed, recent literature has shown that individuals with ASD, and those who experience high-levels of ASD-related traits use a variety of compensatory behaviors, causing them to perform as well as control groups in some studies. For example, many individuals with ASD learn general social rules that allow them to solve ToM tasks (Lai et al., 2017). A study by Livingston and colleagues (2019) found that individuals with ASD who showed deficits in ToM tasks, were nonetheless able to overcome social challenges presented in the context of the Autism Diagnostic Observation Schedule (Lord et al., 2000). In contrast to what would be expected by the social motivation hypothesis, these individuals used compensatory strategies to engage in social interactions (e.g. planning and rehearsing social interactions, using props, suppressing atypical behaviors, engaging in helpful behavior to get others to like them, etc.). Under the social motivation hypothesis framework, if one is not motivated to engage in social interactions, then one has no need to develop potentially costly compensatory behaviors for the purpose of gaining purely social rewards (e.g. friendships, smiles, social approval). These types of compensatory findings sit in contrast to the predictions proposed by the social motivation hypothesis (Jaswal & Akhtar, 2019; Livingston et al., 2019).

Another critique of the social motivation hypothesis is that the behavioral differences thought to be caused by social motivation deficits may have simpler explanations. Instead of a complex explanation that involves early social deficits leading to downstream behavioral changes across a long period of time, critiques suggest that simple differences in motor control can be attributed to the social differences seen in ASD. Many of the claims made by the social motivation hypothesis suggest that individuals with ASD engage in less ‘socially motivated’ actions like eye-gaze, maintenance of joint attention, or declarative pointing (Abrams et al., 2013; Chevallier, et al., 2012; Elsabbagh et al., 2012). For example, many studies find that individuals with ASD engage in less declarative pointing (i.e., to share an experience) and more in imperative pointing (i.e., to obtain something; Baron-Cohen, 1989; Mundy, Sigman, Ungerer & Sherman, 1986). However, on average individuals with ASD point less often in general, especially children (Baron-Cohen, 1989; Robins, Fein, Barton & Green, 2001). Additionally, this lack of pointing can be easily explained by the well-documented finding that individuals with ASD have difficulties performing and coordinating intentional movements (i.e., movements that are not reactive, such as removing a hand from a burning stove) across their lifespan (Bhat, Landa & Galloway, 2011; Fournier, Hass, Naik, Lodha & Cauraugh, 2010; Grandin, 1992; MacDonald, Lord & Ulrich, 2014). Thus, instead of lacking social motivation, it may be the case that individuals with ASD simply have greater difficulty performing these actions, and therefore engage in them less frequently.

A similar explanation may also apply to other social behavioral deficits such as eye-contact. Interestingly, more socially competent individuals with ASD spend more time observing a speaker's mouth compared to their eyes, suggesting that individuals with ASD might process social information better through speech than through eye gaze (Klin et al., 2002). Moreover, self-reports from individuals with ASD suggest that maintaining eye-contact is stressful and disrupts the processing of verbal information (Robledo, Donnellan & Strandt-Conroy, 2012). Thus, many of the 'deficient' social behaviors seen in individuals with ASD may be attributed to more basic explanations (e.g., motor control ability, trying to avoid stressful situations, etc.). Taken together, the social motivation hypothesis may be little more than a secondary explanation for phenomena that have more basic explanations.

An additional difficulty for the social motivation hypothesis is that when researchers report asking individuals with ASD if they are motivated to engage in social interactions, the vast majority indicate they wish to participate more fully in social activities (Biklen, 2005). For example, while some studies have claimed that individuals with ASD have no friends (Howlin et al., 2004; Sedgewick et al., 2016; Taheri et al., 2016), a meta-analysis by Mendelson, Gates and Lerner (2016) instead finds that the vast majority of individuals with ASD report at least one friend. Moreover, Jaswal and Akhtar (2019) have suggested that for people with ASD, having fewer friends might be expected after a lifetime of people misunderstanding them and misinterpreting their actions. Such a life history might lead some individuals with ASD to no longer enjoy or seek out social interactions because the pain of social rejection may be greater than the pain of loneliness. This idea has some merit. For example, individuals with Parkinson's Disease tend to speak in a slower and more controlled manner than do people without the disease (Benke, Hohenstein, Poewe & Butterworth, 2000). This may cause others to experience Parkinson's patients as less supportive and less interested in relationships compared to those without Parkinson's (Hemmesch, Tickle-Degnen & Zebrowitz, 2009). Indeed, even clinical practitioners tend to mischaracterize those with Parkinson's as less extraverted, more neurotic, less socially interested, and less cognitively competent then they actually are (Lyons, Tickle-Degnen, Henry & Cohn, 2004; Tickle-Degnen & Lyons, 2004; Tickle-Degnen, Zebrowitz & Ma, 2011). Thus, misinterpretation of the social cues individuals with ASD produce may lead to negative social outcomes, including fewer and lower quality friendships compared to non-clinical groups (Mendelson et al., 2016).

A final critique of the social motivation hypothesis is that the findings that support the social motivation hypothesis may better fit a probabilistic learning framework (Scott Van Zeeland et al., 2010; Vernetti et al., 2018b). For example, Vernetti and colleagues (2018b) found that in toddlers with ASD, reward-seeking behavior towards social stimuli in an eye-tracking task was intact and thereby inconsistent with the predictions of the social motivation hypothesis. In the task toddlers had the choice between two images on a screen (toy or face) and they made their selection by gazing at one of the images. They were then rewarded with a video of the image they looked at. Results showed that toddlers with ASD stared longer at videos of faces than of toys and smiled more at the faces then at the toys much like the non-clinical group. However, when the social task had a probabilistic learning element in it (i.e., rewards were not always gaze-contingent), toddlers with ASD then showed a lack of preference for social rewards. This led researchers to propose that difficulty processing event statistics, rather than social motivation might be driving these effects.

Taken together, there are many reasons to question both the findings and theoretical underpinnings of the social motivation hypothesis. Yet despite such criticisms the social motivation hypothesis remains a highly influential hypothesis that is widely cited (Bottini, 2018; Chevallier et al., 2012; Uljarević, et al., 2019). As such, the assumptions of this hypothesis should be considered and further tested. Next, I investigate some cognitively based learning models of ASD that stand in contrast to the social motivation hypothesis.

1.2 Learning and Decision Making

Other literature takes a more cognitive view of ASD, suggesting that basic cognitive mechanisms rather than social reward deficits are associated with symptoms. Specifically, this work has suggested that cognitive abilities, such as cognitive-processing or learning ability are causal factors in the altered developmental trajectories and atypical behaviors found in individuals with ASD. Thus, cognitive theories posit that inherent deficits in cognitive mechanisms (e.g., processing biases, probabilistic learning) cause reduced interest in and ability to learn from social interactions. Two major classes of cognitive hypotheses within this framework are 'cognitive processing' hypotheses, which generally suggest differences in processing biases account for ASD symptoms (e.g., the weak central coherence account; Frith, 2003; Happé & Frith, 2006) and probabilistic learning hypotheses that suggest reduced ability to understand environmental event statistics result in ASD symptoms (Crewther & Crewther 2014; Pellicano & Burr, 2012; Sevgi, Diaconescu, Henco, Tittgemeyer & Schilbach, 2020; Solomon et al., 2011; Tzovara, Korn & Bach 2018).

1.2.1 Weak Central Coherence Hypothesis

The idea that people with ASD perceive and process the world in atypical ways has historically been a prominent cognitive theory in autism research. For example, research shows that people with ASD and those who report more ASD-related symptoms may have a bias toward “local” (perceiving fine details) versus “global” processing (tendency to see the big picture; Bolis & Schilbach 2018; Burghoorn, Dingemanse, van Lier & van Leeuwen, 2018; Crewther & Crewther, 2014; Frith & Happé, 1994; Grinter, Van Beek, Maybery & Badcock, 2009; Happé & Frith, 2006; López, Donnelly, Hadwin & Leekam, 2004; Morgan, Maybery & Durkin, 2003; Pellicano et al., 2011; Van der Hallen, Chamberlain, de-Wit & Wagemans, 2018). This idea suggests that individuals with ASD have difficulty integrating details of a stimulus to obtain a gestalt or holistic impression leading to poor “central coherence” (Frith, 2003; Kana et al., 2013; Lovaas, Schreibman, Koegel, & Rhem, 1971; Van Boxtel & Lu, 2013).

Face processing is one domain in which holistic processing is important. People use holistic face processing skills every day in the context of day to day social interactions across the lifespan (Curby, Johnson & Tyson, 2012; Enea & Iancu, 2016; Kovács, Knakker, Hermann, Kovács & Vidnyánszky, 2017; Morgan & Hills, 2019). Face processing skills start developing early in infancy and impact how people understand emotions and social cues, as well as how they react in social situations. (Ke, Whalon & Yun, 2018; Kovács, Knakker, Hermann, Kovács & Vidnyánszky, 2017; Morgan & Hills, 2019; Repacholi, Meltzoff, Toub & Ruba, 2016; Wang, 2019). When face processing is disrupted, as other clinical disorders such as schizophrenia, this disruption may lead to social difficulty (Chamberlain, McManus, Riley, Rankin & Brunswick, 2013; Dawson et al., 2005; De Crescenzo et al., 2019; Earls, Curran & Mittal, 2016; Lang, Lopez, Stahl, Tchanturia & Treasure, 2014; Lopez, Tchanturia, Stahl & Treasure, 2008; Silverstein et al., 2014).

The presence of processing biases in ASD has generated several hypotheses about autism. One of the more prevalent hypotheses is known as the weak central coherence hypothesis (Frith, 2003; Happé & Frith, 2006). The idea behind this hypothesis is that the cognitive systems responsible for integrating individual points of information into a ‘whole’ context or gestalt is weak which results in a cognitive bias towards local information (individual aspects of a context) versus global or wholistic aspects of the entire context (Happé & Frith, 2006; Plaisted, Saksida, Alcántara & Weisblatt, 2003). From a neurological perspective, proponents of the ‘weak central coherence’ hypothesis point to studies that have shown there is poor neural connectivity between interhemispheric regions of the brain (e.g., distal and proximal regions including the frontal lobe and parietal lobe; Belmonte, Allen, Beckel-Mitchener, Boulanger, Carper & Webb, 2004; Just, Cherkassky, Keller & Minshew, 2004; Rane, Cochran, Hodge, Haselgrove, Kennedy & Frazier, 2015), while intrahemispheric neural connectivity is increased (Belmonte et al., 2004; Rane et al., 2015; Rubenstein & Merzenich, 2003; Vissers, Cohen & Geurts, 2012;). Such findings suggest that these neural differences are, at least in part, responsible for the local processing biases seen in individuals with ASD (Happé, 2005; Happé & Frith, 2006 Just et al., 2004). This viewpoint has led to the central prediction that individuals with ASD should preferentially use local versus global processing pathways (Bolis & Schilbach 2018; Frith & Happé, 1994). This prediction must be true for the weak central coherence hypothesis to hold any merit, as it is the main explanation for the social symptoms associated with ASD.

Additionally, if theories such as the central coherence hypothesis are to be supported, one should predict processing biases to occur regardless of domain being processed (e.g. social and non-social domains). This idea has been supported by research finding that individuals with ASD and those who report high levels of ASD-related traits in the general population, often have enhanced local processing and reduced global processing skill compared to those without ASD, or those with fewer traits (Burghoorn, Dingemanse, van Lier & van Leeuwen, 2018; Crewther & Crewther, 2014; Grinter, Van Beek, Maybery & Badcock, 2009; Happé & Frith, 2006; Pellicano et al., 2011). Moreover, literature in this area has grown considerably over time, suggesting that this finding is generally reliable (Simmons, Robertson, McKay, Toal, McAleer & Pollick, 2009). Much of the literature assesses this hypothesis using non-social domain tasks like the "embedded figures" task (e.g., Burghoorn, et al., 2018; Van der Hallen, et al., 2018).

In addition, other tasks such as the block design subscale of the Wechsler Intelligence Scales, Mental Rotation task, Navon Figures task and the “homograph task” have also provided strong support for the idea that individuals with ASD, as well as those who report ASD-related traits, perform better on tasks that require local processing, rather global processing (Conson et al., 2013; Deruelle, Rondan, Gepner & Fagot, 2006; Grinter et al., 2009; Jolliffe & Baron-Cohen, 1999; Pellicano, Maybery, Durkin & Maley, 2006; Snowling & Frith, 1989).

This preference for local processing in ASD can also be found in social domains, using social versions of embedded figures and similar tasks (Hobson, Ouston & Lee, 1988; Russell-Smith, Maybery, Bayliss & Sng, 2012), as well as other methodologies (Behrmann et al., 2006; Skorich et al., 2016). An interesting study by Skorich and colleagues (2016) found a positive relationship between the number of autistic traits participants endorsed and the degree of local social categorization that occurred. Additionally, this relationship was predictive of the ability to make mental state inferences. This is an important link, as it shows that perceptual preferences not only affect social cognitive skills but may also affect the outcomes of social interactions.

Despite its supporting evidence, the theory is not without criticisms. One important criticism is that weak central coherence is not universally present in all individuals with ASD or those in the general population who show many ASD-related traits. Indeed, some people show fully intact global processing skills (Hayward, Fenerci & Ristic, 2018; Hoy et al., 2004; Mottron, Burack, Iarocci, Belleville & Enns, 2003). This is further emphasized in a meta-analysis by Muth, Hönekopp and Falter (2014), which found that the effect sizes of performances for tasks like EFT, Mental Rotation task, Navon Figures task, and Block Design task were much smaller than expected and heterogeneity was high. Worse yet, when they removed outliers in the data, the enhanced performance of individuals with ASD disappeared. The large degree of heterogeneity in the processes that underlie ASD symptoms weaken the claims made by proponents of the weak central coherence hypothesis and suggest that, at best, they can only explain some features of this disorder.

Another possibility that researchers have proposed is that enhanced local processing in the context of decreased global processing might not be evidence for a real cause of the disorder and might instead reflect another cognitive impairment (Bernardino et al., 2012; Gómez et al., 2014; Hayward, Fenerci & Ristic, 2018; Muth et al., 2014). For example, Bernardino and colleagues (2012) found that group differences between individuals with ASD and controls in local processing tasks disappeared when groups were matched for intellectual disabilities. Indeed, it might be the case that studies that ignore, or do not properly control for individual differences are the ones reporting the largest effects for these theories.

Finally, Pellicano and Burr (2012) have suggested that the weak central coherence findings might be better explained in the framework of probabilistic learning theories, with the focus being more related to the ability to learn from probabilistically reinforced contingencies, rather than local versus global processing. Both theories suggest mechanisms to explain the differences in how individuals integrate information from the environment, but Pellicano and Burr (2012) have suggested predictive learning models might fit the data better. This is further supported by Gómez and colleagues (2014) who have suggested that neurological models of ASD cannot be explained by simple processing biases, but require a probabilistic explanation either in conjunction with or as the main explanation for the social symptoms of ASD.

1.2.2 Probabilistic Learning Hypotheses

Reinforcement learning has been described as the process by which an individual learns stimulus-feedback predictions through trial and error (Atkinson & Wickens, 1971; Cohen, 2008; Erev, Bereby-Meyer & Roth, 1999; Erev & Roth, 1998; Sutton & Barto, 2018). This process involves exploring actions and evaluating their outcomes. These predictions are then used to guide behavior. More specifically, this process involves learning action-outcome associations implicitly from the environment, as well as adopting the optimal balance of “exploration” and “exploitation” of behavioral options to achieve maximum reward (Sutton & Barto, 2018). Under reinforcement learning models, the consistency with which an action is rewarded, and the value of the reward drives the speed of learning (Evans & Over, 1996; Kaelbling, Littman & Moore, 1996; Niv, 2009). Based on this idea, more reliably reinforced actions (those with deterministic reinforcement schedules) lead to faster learning of an action-outcome contingency than do less reliably reinforced actions (more probabilistic; Bereby-Meyer & Roth, 2006; Erev et al., 1999).

As the majority of learning, developing contingencies and forming beliefs throughout life is not perfectly reliable or certain, cognitive research in learning has sought to create models for this process, which has led to a series of probabilistic models (Chanter, Tenenbaum & Yuille, 2006). These probabilistic learning models have been used to explain human learning for decades. While most of the early research supporting probabilistic learning models showed evidence that humans learn probabilistic contingencies from both the stimuli and feedback in non-social environments (Evans & Over, 1996; Manktelow, Sutherland & Over, 1995; Oaksford & Chater, 2001), more recent work shows that it applies in social environments as well (Gaigg, & Bowler, 2007; Solomon et al., 2015; Solomon et al., 2011; Vascon et al., 2014). Specifically, the ability to learn from probabilistically reinforced responses is important to many different aspects of people's social ability including the understanding of social signals (e.g., approval, invitation, etc.), detecting and responding to facial expressions and emotions, inferring appropriate social behavior within a social context, and responding to social requests (Gaigg, & Bowler, 2007; Frank, 2014; Li, Xu, Gan, Tan & Lim, 2017; Stevens, Peters, Abraham & Hermann, 2014; Vascon et al., 2014; Vitale, Williams, Johnston & Boccignone, 2014). However, more recent research has expanded the scope of this work to ask how individual differences in the ability to learn from environmental stimuli influence social ability (Kaufman et al., 2010; Santesso et al., 2008; van den Bos, Crone & Güroğlu, 2012; Yechiam et al., 2010). Generally, this work tends to suggest that the better people are at learning from probabilistic contingencies, the better they should perform on tasks with elements of ambiguity, such as social interactions.

One group of individuals who appear to show atypical probabilistic learning mechanisms are individuals with ASD. An interesting and reasonably consistent finding is that while those who report more ASD-traits, or are diagnosed with ASD, learn from perfectly reliable "deterministic" feedback at similar rates compared to those who report fewer traits, differences appear when feedback becomes less reliable (i.e., probabilistic; D'Cruz et al., 2013; Lawson, 2017; Palmer, Lawson & Hohwy, 2017; Pellicano & Burr, 2012; Solomon et al., 2015; Solomon et al., 2011; Schuetze, Rohr, Dewey, McCrimmon

& Bray, 2017;Van Boxtel & Lu, 2013). Unreliable feedback is naturally more difficult for people to learn from (Chater et al., 2006; Oaksford & Chater, 2001; Shepard, 1987), but ASD-related traits seem to enhance the difficulty of learning under probabilistic feedback contingencies (Amoruso et al., 2019; D'Cruz et al., 2013; Gaigg, & Bowler, 2007; Lawson, 2017; Solomon et al., 2015).

Interestingly, people's ability to learn from probabilistic feedback appears to be affected by the type of feedback from which they learn. For example, evidence shows that individuals with ASD performed worse on a probabilistic learning task when the feedback was social in nature (faces), compared to non-clinical groups. The same study found no performance differences for a monetary feedback condition (Van Zeeland, Dapretto, Ghahremani, Poldrack & Bookheimer, 2010). These results have been replicated in similar studies (Lin et al., 2012), leading researchers to suggest that individuals with ASD have impaired responses to social stimuli (Chambon et al., 2017; Dawson, Meltzoff, Osterling, Rinaldi & Brown, 1998; Lin et al., 2012; Scott-Van Zeeland et al., 2010). However, given that in at least some studies, individuals with ASD both report and show intact responses to social reward, it may be the case that the underlying difficulties are more related to learning under probabilistic reinforcement. There is some support for this idea in the literature. Specifically, research has found no differences in performance between groups when a task is simple and contingencies are easy to learn but demonstrated that differences arise when task contexts become more complex and therefore ambiguous (Yechiam et al., 2010). Thus, it may be that it is the ambiguous nature of the social situations, and not the social feedback itself that causes the social deficits seen individual with ASD. If this is the case, then a probabilistic framework for ASD is likely the most appropriate approach.

Demonstrating the impact of ambiguity and reliability, a study by Sevgi and colleagues (2020), found that there was a relationship in a general-population sample between the number of endorsed ASD-related traits and participants' ability to learn during periods of high task uncertainty. Specifically, individuals who reported more ASD-related traits made poor use of environmental cues and performed worse on an associative learning task, compared to individuals who reported fewer ASD-traits. One reason for these performance differences, according to the researchers, was that low-symptom participants appeared to update their expectations about the environmental contingencies more often. Specifically, when environmental contingencies were stable, these low-symptom participants relied on cues provided by the environment but when these cues became less reliable these participants explored the possibility that new contingencies were in operation. In contrast, participants who reported higher levels of ASD-traits showed much more difficulty adapting to changing environmental contingencies.

The findings of Sevgi and colleagues (2020) also supports some probabilistic learning hypotheses that further clarify what constitutes this atypical learning, suggesting that this atypical probabilistic learning in individuals with ASD are driven by an altered use of environmental information to form contingencies (Pellicano & Burr, 2012). The idea is that individuals with ASD might inappropriately make estimates about the volatility of the environment and the cues it provides (Lawson, Rees, & Friston, 2014). This may lead to difficulty interpreting and learning from new information because the estimates/expected outcomes associated with that information may not be updated accurately. That is, because contingencies in environments in the real world often change, individuals often must weigh new information in the context of prior expectations to come up with new/updated contingencies. Supporting this, studies have found that individuals who are diagnosed with ASD are more likely to over-estimate the volatility of the environment which results in impairments in the ability to learn stable expectations (Lawson, 2017; Palmer, Lawson & Hohwy, 2017). These findings not only apply to clinical populations but also to individuals within the general population (Bolis & Schilbach 2018; Sevgi et al., 2020).

Probabilistic learning challenges are not limited to the domain of learning new contingencies but are also found in the process of unlearning old contingencies and replacing them with new ones. For example, one study showed that in a probabilistic reversal-learning task, individuals who were diagnosed with ASD had trouble sticking to newly learned contingencies and reverted back to behaviors consistent with old contingencies more often than did participants without such diagnoses (D'Cruz et al., 2013, South et al., 2014). This type of behavior has been likened to the rigid and repetitive behavior people with ASD often show in both the social and non-social domains (South, Ozonoff & McMahon, 2005). Thus, probabilistic learning difficulties may explain both the social behavior deficits and non-social behavioral impairments in ASD.

Another strength to the probabilistic learning framework is that it can explain some of the non-social aspects of ASD. For example, individuals with ASD learn fear associations more slowly than do those without such diagnoses when the to-be-learned association is less reliably reinforced (Chamberlain et al., 2013; Gaigg, & Bowler, 2007). In studies that have a deterministic link between the conditioned stimulus and the unconditioned stimulus, individuals with ASD learn the association between the two at the same rates as control groups (Bernier, Dawson, Panagiotides & Webb, 2005; Sterling et al., 2013). These findings emphasize how deficits in probabilistic learning mechanisms may underpin a variety of social and non-social behaviors across the autism spectrum.

Even though these findings seem as though they might explain many of the social and non-social deficits in ASD, much of this work suffers from methodological limitations. For one, some of these findings rely on a common probabilistic learning task (see Frank, 2005), that suffers from stimulus-related irregularities that can cause poor test-retest reliability as well as confound findings (Baker et al., 2013; Schutte et al., 2017). In addition, researchers have defined “social” and “non-social” stimuli in highly inconsistent ways. For example, stimuli defined as ‘social’ include many non-social elements, like flashing lights (Birmingham, Bischof & Kingstone, 2009; Chambon et al., 2017; Robic et al., 2016), which can co-occur thus confounding results (social or non-social elements). Still, other studies have relied on non-social objects such as emojis (Weiß, Mussel & Hewig, 2019), meaning that results are not necessarily strong tests of response differences to social stimuli. Thus, prior results might be confounded by the types of “social” stimuli used across different tasks (Aberg et al., 2016; Chambon et al., 2017).

An additional concern in this literature domain is that not all studies find support for probabilistic learning deficits in individuals with ASD (Brown, Aczel, Jiménez, Kaufman & Grant, 2010; Nemeth et al., 2014; South et al., 2014). For example, one study found that that there were no differences in Iowa Gambling Task performance between children with and without ASD (Faja, Murias, Beauchaine, & Dawson, 2013). Another found that children with ASD develop and update their contingencies from probabilistic environments at a similar rate to controls (Manning, Kilner, Neil, Karaminis & Pellicano, 2017). Lastly, South and colleagues (2014) found improved performance in participants with ASD during the Iowa Gambling Task, such that individuals in the ASD group were quicker to learn the deck contingencies and more likely to pick the advantageous deck, than were those in the control group. These inconsistencies suggest the possibility that learning mechanisms are intact in at least some people with ASD, although methodological differences might be responsible for these divergent results.

1.3 What can we learn from these prominent autism hypotheses?

This diverse set of theories rooted in learning mechanisms suggests several common themes associated with ASD-related traits. First, all these theories suggest that individuals with ASD have deficits in learning that are the result of alterations in how they incorporate information from the environment. Second, many of the studies described in this section also seem to suggest that individuals with ASD or ASD-related traits learn better from/show a preference for non-social stimuli and non-social feedback over social stimuli and social feedback. One explanation for this suggestion is that the social environment is more complex, more ambiguous, and less predictable than the non-social environment. Therefore, it is more difficult to learn from social feedback and more difficult to develop a sense of the “value” or “utility” of this feedback, compared to non-social feedback. Thus, learning deficits are most prominent when learning from ambiguous stimuli or in contexts with an element of unpredictability, as is the case with both probabilistic feedback during contingency learning tasks and social feedback in the social environment. Because cause and effect relationships are weaker in social environments, the behavioral differences become more remarkable and prominent in the social domain between those with and without ASD.

If people diagnosed with ASD and those that experience symptoms of ASD struggle to learn from probabilistic contingencies, this would explain why the primary symptoms of this disorder are social deficits. More specifically, in order to function in the world, it is necessary to understand the naturally occurring, probabilistically reinforced and ambiguous contingencies that operate within different social environments and across different social partners (Pellicano & Burr, 2012; Robic et al., 2015). For example, nonverbal social cues are particularly ambiguous both because their configuration depends on a sender's physical characteristics and because individual senders use these cues differently in different situations. There is also a high degree of heterogeneity in the use of certain cues in particular types of situations (Bartz, Zaki, Bolger &Ochsner, 2011; Derks, Bos & Von Grumbkow, 2007; Tanis & Postmes, 2003).

Furthermore, if stimuli (e.g., social situations) become too ambiguous, people must tolerate a certain degree of uncertainty (i.e., prediction error, surprise) to properly learn contingencies. If one views previous findings not from the proposed theoretical perspective (e.g., social motivation hypothesis, weak central coherence hypothesis), but instead from a probabilistic framework, the study data suggest that many of the ASD-related social symptoms are better explained as a product of altered cognitive processes (Pellicano & Burr, 2012; Van de Cruys et al., 2014). As previously stated, the less deterministic an environment is, the more difficulty individuals have learning the contingencies within it (Evans & Over, 1996; Manktelow, Sutherland & Over, 1995; Oaksford & Chater, 2001). Thus, the fact that the social world is less deterministic than the physical world (Derks, Bos & Von Grumbkow, 2007; Wyer & Srull, 1986) might be a better explanation of ASD-related social deficits than either reduced social motivation or weak central coherence. Specifically, the naturally probabilistic occurrence of social rewards (Fiedler, 1996) may make them more difficult to learn and therefore less valuable to those with ASD (Bottini, 2018; Chevallier, et al., 2012). In addition, the fact that they are more ambiguous may also make them more difficult to contextualize and generalize for those with ASD.

1.3.1 General Theoretical and Methodological Limitations

Despite their long history in the world of autism research, these theories share methodological limitations. One of the most glaring limitations across the research field is the use of small participant samples (e.g., Bottini, 2018; Dawson et al., 1998; Lin et al., 2012; Manning et al., 2017; Muth et al., 2014; Sevgi et al., 2020; Solomon et al., 2015; Solomon et al., 2011, Van der Hallen et al., 2018). Indeed, several research groups have noted that small underpowered samples can have serious effects on the likelihood that a statistically significant finding reflects a true effect (Button et al., 2013; Camerer et al., 2018; Kühberger, Fritz & Scherndl, 2014; Simonsohn, 2015). In addition, many of the studies in this literature have been conducted using non-double blind designs, in which participants are recruited based on the presence/absence of particular characteristics and then tested by researchers who know both the study group and the hypotheses. Evidence shows that researchers can inadvertently communicate this knowledge to participants, thereby serving to magnify group differences in unintended ways (Canter, Hammond & Youngs, 2013; Gilder & Heerey, 2018; Rosenthal, 1994; Sheldrake, 1998). Thus, the field should work toward replication efforts using larger samples, double blind methods and methods that are more resistant to potential confounds.

There are also several theoretical limitations to these theories. The most serious of these relates to the generalization of research findings to everyday life. Much of the literature that reports differences between participants with and without ASD/ASD-traits links these differences theoretically to social function, and specifically to the deficits that most prominently characterize ASD. Unfortunately, however, the previous research offers few direct tests of the links between symptoms and/or cognitive function and natural, real-world social behavior. Additionally, the few direct tests that have occurred have typically included young children or early adolescents or have focused on constrained situations in which specific set of "social skills" can be measured (Bauminger, 2002; Dissanayake & Crossley, 1996; McLaughlin-Cheng, 1998; Van Wijngaarden-Cremers et al., 2014; White, Keonig & Scahill, 2007). Thus, these links are mostly theoretical. Empirically linking the theoretical cognitive and motivational underpinnings of social behavior with direct face-to-face social behavior would greatly strengthen these arguments and provide additional research and therapeutic targets. Without this, conclusions about how the empirical findings relate to actual behavior are merely theoretical.

A second issue in this literature is that there are many inconsistent findings within the context of each theory. That is, some studies confirm predictions whereas others find inconclusive or contrary results (Bottini, 2018; Chevallier, et al., 2012; Muth et al., 2014;

Obeid, Brooks, Powers, Gillespie-Lynch & Lum, 2016; Van der Hallen et al., 2018). Some of the inconsistencies, and heterogeneity of autism-symptomatology have been explained by the possibility that there are different ‘phenotypes’ of autism, such that no one theory might be able to explain the full spectrum of autism but each might be able to explain certain ‘phenotypes’ of autism (Charman et al., 2001; Happé & Ronald, 2008; Ronald & Hoekstra, 2011). Nonetheless, the existence of different ‘types’ of autism, and what those types might be, is currently unknown. Until such clarification occurs, ambiguity and inconsistency will need to be tolerated.

1.4 Current Research

The empirical chapters of this dissertation test several hypotheses related to understanding the relationships between social motivation, learning mechanisms and real-life social behavior. All the samples reported here consist of members of the general population. I made this decision for several reasons. One reason was individuals in the general population are less likely to have co-morbidities, such as social anxiety and depression, as those who are clinically diagnosed with ASD and the effects of these co-morbidities can be difficult to disentangle in the literature (Mazzone, Ruta & Reale, 2012; Volkmar, State & Klin, 2009). More specifically, across the general population at any given point, common disorders such as anxiety and depression are 4.4% and 3.6% respectively, whereas in the adult population with ASD, the rates of these disorders, at any given point, are 27% and 33% respectively (Hollocks, Lerh, Magiati, Meiser-Stedman & Brugha, 2019; World Health Organization, 2017). Thus, members of the general population are far less likely to be impacted by clinically significant anxiety and depression compared to those diagnosed with ASDs. Additionally, the use of a general population sample allows large double blinded studies, thereby avoiding issues with underpowered studies that might be impacted by experimenter effects. Lastly, evidence suggests that autism symptoms occur along a spectrum, such that endorsement of those traits confers risk for deficits in proportion to the number of endorsed traits (Constantino, 2011; Horder, Wilson, Mendez & Murphy, 2014; Ingersoll, 2010; Jones et al., 2013; Sevgi et al., 2020), rather than a more binary categorization that would sharply differentiate those with and without diagnoses (Jones et al., 2013; Lauritsen, 2013; Volkmar et al., 2009).

To measure individuals' autism traits across the spectrum, all participants completed the Autism-spectrum Quotient scale (Baron-Cohen, et al., 2001). This scale is commonly used across the literature to measure autism-traits, and while it is a non-clinical scale, it has been found that individuals who score 32 or greater on it, out of a possible score of 50, have an 80% likelihood of meeting diagnostic the criteria for an ASD (Baron-Cohen, et al., 2001). This suggests it has reasonable validity for the traits it is measuring.

Thus, from a methodological standpoint, the use of a general population sample enhances statistical power and reduces possible confounds. However, the use of non-clinical samples precludes certain conclusions about autism as a disorder more generally. I discuss this limitation further in the discussion section (Chapter 6) of this work.

The empirical chapters in this work are organized by the theoretical questions being answered, rather than by specific "studies". Each chapter investigates different predictions made by the major theories of autism discussed in this introduction (i.e., the social motivation hypothesis, weak central coherence hypothesis and probabilistic learning theories). I chose this organization because many of the samples I analyze speak to multiple theoretical questions. This layout choice has led to some samples of participants being referenced across several chapters, as participants often completed a series of tasks that help answer questions across several prominent ASD hypotheses. Figure 1 presents a conceptualization of how the participant samples are analyzed.

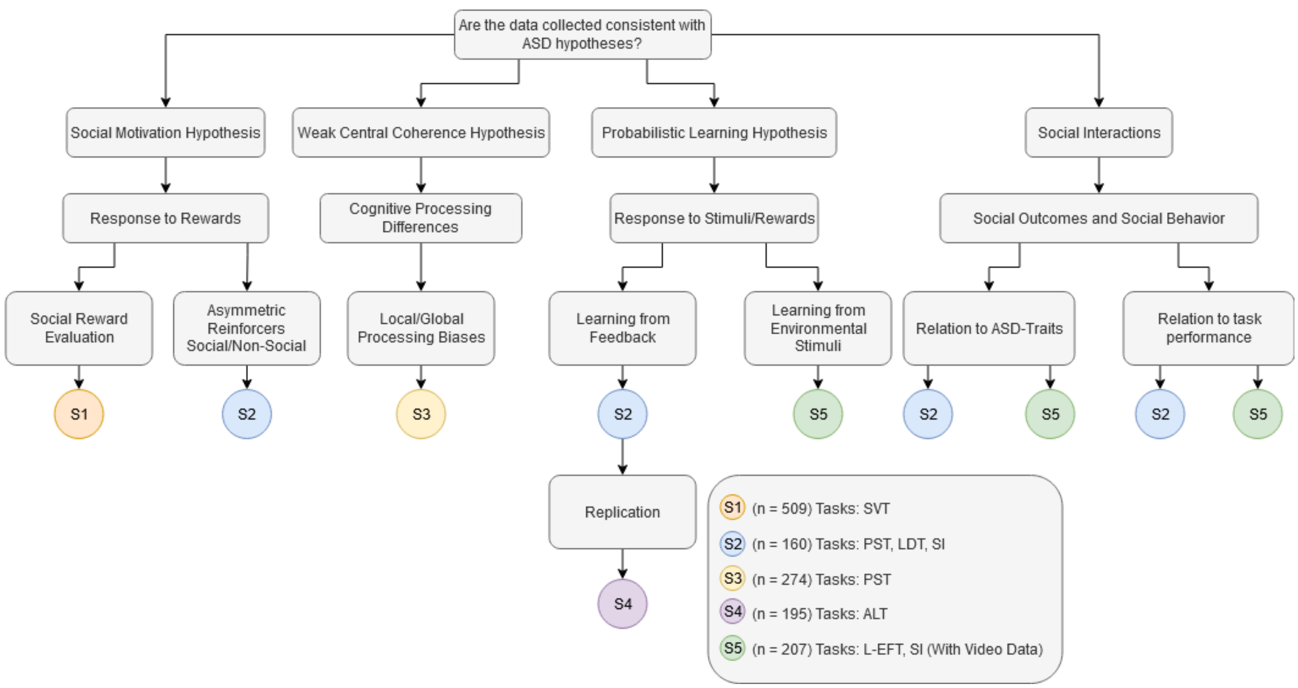

Figure 1. *Schematic of Dissertation Organization.*

Note: ALT = Associative Learning Task, ASD = Autism Spectrum Disorder, L-EFT = Leuven Embedded Figures Task, LDT = Line Discrimination Task, PST = Probabilistic Selection Task, SI = Social Interaction, SVT = Smile Valuation Task

In Chapter 2, I test two ideas related to the social motivation hypothesis. According to the predictions of this hypothesis, I would expect individuals who report higher-levels of ASD-related traits, especially in the domains of social skill and communication difficulties, to be less sensitive to social rewards compared to non-social rewards. To test this idea, I first examine these relationships in individuals from the general population to see whether self-reported autism-spectrum traits relate to sensitivity to social and non-social reinforcers in a reward sensitivity task (Pizzagalli, Jahn, & O'Shea, 2005). Second, I test the hypothesis that individuals who report more ASD-related traits will show evidence of reduced perceptions of subjective value or utility for social versus non-social rewards. The goal of this hypothesis was to test whether, in the general population, there is a link between self-reported autism-spectrum traits and the degree to which specific social reinforcers (genuine and polite smiles) bias participants' decisions in a smile valuation task (Heerey & Gilder, 2019). If data are consistent with these predictions, it will provide strong evidence for the social motivation hypothesis and expand upon the literature in that field.

Chapter 3 examines the weak central coherence hypothesis suggestion that global versus local processing biases differ amongst those reporting high and low levels of ASD traits. Hypotheses that suggest weak central coherence as an explanation for ASD-related traits predict that individuals who report more ASD traits will have an advantage over those with fewer traits in terms of their ability to use local, relative to global processing pathways to parse complex stimuli. My goal is to test whether, in the general population, there is a link between self-reported autism-spectrum traits and participants' local processing ability using the Leuven Embedded Figures Task (de-Wit, et al., 2017). In this study, I use a larger variety of ASD-related trait measures, along with an additional measure of social ability: the Reading the Mind in the Eyes Test (Baron-Cohen, Wheelwright, Hill, Raste & Plumb, 2001).

Chapter 4 examines the predictions of probabilistic learning hypotheses which suggest that ASD traits are the product of altered probabilistic learning mechanisms. These hypotheses predict that individuals who report more ASD-related traits will learn better from non-social relative to social rewards and from reinforcement schedules that are more deterministic rather than probabilistic. To test this hypothesis, participants completed a probabilistic selection task (Frank, Seeberger & O'Reilly, 2004; Solomon et al., 2011) with social and non-social reinforcement. Additionally, I examined whether individuals who report higher-levels of ASD-related traits have deficits in the ability to make predictions and update their contingencies using social versus non-social cues during periods of volatility. To test this hypothesis, participants completed an associative learning task (Behrens, et al., 2008; Sevgi, et al., 2020) with social and non-social reinforcement blocks. If data are consistent with predictions it will demonstrate both evidence about the nature and cognitive underpinnings of social behavior, as well as provide a mechanism for understanding the social deficits that individuals with ASD manifest.

Finally, in Chapter 5, I aim to relate cognitive performance to naturalistic social behavior. I do this by asking participants to complete a short, naturalistic social interaction with a partner, obtaining both participants ratings of interaction quality and liking for the partner, along with video recordings of participants’ social behavior. The data from these partner-ratings and behavior are then correlated with relevant performance metrics on the cognitive tasks. These data will allow us to better understand both the specific social outcomes associated with ASD, as well as the larger associations between cognitive performance and real social ability.

The overarching goal for this dissertation, is to find out which theories of autism the data in this dissertation best support and how these theories relate to social behavior. I also aim to test these ideas using large participant samples and double-blind research methods. This dissertation will provide evidence about what underlying general mechanisms drive social behavior and differences in social ability more generally. This will allow for future research to be directed towards theories that provide promising avenues for explaining the social deficits associated with ASD. Thus, I aim to lay the groundwork for how cognitive processes underpin and support people's social behaviors.

2 Testing the Social Motivation Hypothesis of Autism

Over the past few decades, theories about motivation, and reward value have been gaining momentum as possible explanations for the symptoms and behaviors associated with ASD-related traits (Chevallier et al., 2012; Damiano, Aloi, Treadway, Bodfish & Dichter, 2012; Senju et al., 2009; Turner-Brown et al., 2011; Wellman et al., 2012). Findings from this literature have largely coalesced into the social motivation theory of autism (Chevallier et al., 2012). The social motivation theory suggests that ASD are the result of early-onset deficits in attention to social stimuli that result in altered response patterns to these stimuli.

In this chapter I investigate two central assumptions based on these theories in a general population sample. First, I address the question of whether individuals who endorse more ASD traits are less sensitive to social rewards compared to non-social rewards, relative to those who endorse fewer ASD traits. Second, I examine whether autism spectrum-traits are associated with how much people value social rewards. Specifically, I predict that those endorsing more ASD-traits should show reduced valuation of social rewards relative to those endorsing fewer traits. Importantly, the studies in this chapter test these ideas using double-blind conditions and well-powered samples.

2.1 Research Question 1: Reward Sensitivity

This study investigated the link between autism-spectrum traits and reward sensitivity in a general undergraduate sample and exposed them to a series of tasks under both social and non-social reinforcement. I examined participants’ general sensitivity to reinforcement using an “asymmetric reinforcement” task (Pizzagalli, Jahn, & O’Shea, 2005) that allowed us to assess the development of response bias in the presence of social versus non-social rewards.

2.2 Methods

2.2.1 Participants

I recruited 160 participants (see Table 1 for demographic characteristics and group comparisons) from the Western Psychology Participant Pool (SONA; N=109) along with a mixed community sample recruited using advertisements and word of mouth (N=51). Sample size was determined by a power analysis (see Appendix B for details; similarly, all sample sizes were selected this way). Participants completed a line-discrimination task alongside a series of questionnaires in the context of a larger study that included a probabilistic learning task and a social interaction, which are described in later chapters (See chapter 4 and chapter 5 respectively). In exchange for participation, participants received partial course credit or a small payment of $15 per study session. All participants also received a small monetary bonus earned in the tasks. Participants completed the task over two study sessions. Of the 160 participants recruited, 75 (47%) participants completed both sessions and the remaining 85 (53%) completed one session. This meant that I was unable to compare performance across sessions for 53% of participants.

I removed 12 participants’ data from analysis due to inattentiveness, defined as failing to receive at least 85% of the available rewards in the task or if participants’ responses were faster than 250ms or slower than 5000ms on more than 30% of trials. I set this criterion to ensure participants attended to enough feedback to learn the task contingencies. I classified participants as endorsing either low or high levels of autism spectrum traits based on a median split of their total score on the Autism-spectrum Quotient (AQ; Baron-Cohen, et al., 2001). I classified participants who scored 17 or lower as “low ASD trait participants” and those who scored above 17 as “high ASD trait participants.” The Western University Nonmedical Ethics Board approved all study procedures and participants documented their informed consent prior to participating.

Table 1. *Participant characteristics and Demographic Information*

AQ Group	High ASD traits (AQ > 17)	Low ASD traits (AQ ≤ 17)	*F*	df	*p*
n	79	81			
Score Range	18-45	6-17			
Sex (Female:Male) *	46:31	45:36	0.28	1,155	.597
Age in years	20.8 (4.4)	21.0 (4.5)	0.13	1,154	.723
Autism-spectrum Quotient					
Total Score	23.7 (5.1)	13.7 (2.4)	250.65	1, 157	<.001
Social Skills	4.0 (2.8)	1.3 (1.4)	61.96	1, 157	<.001
Attention Shifting	6.3 (1.8)	3.6 (1.4)	107.73	1, 157	<.001
Attention to Detail	6.56 (2.0)	5.36 (2.0)	14.32	1, 157	<.001
Communication	3.7 (1.9)	1.7 (1.4)	61.69	1, 157	<.001
Imagination	3.2 (1.8)	1.9 (1.3)	25.22	1, 157	<.001
Big Five Inventory					
Extraversion	28.7 (5.7)	22.1 (7.4)	9.72	1, 157	.003
Agreeableness	31.8 (5.0)	34.4 (6.1)	2.42	1, 157	.128
Conscientiousness	33.5 (4.1)	35.8 (4.4)	3.10	1, 157	.086
Neuroticism	26.5 (7.9)	24.8 (6.3)	0.57	1, 157	.454
Openness	35.2 (5.1)	37.3 (4.9)	1.83	1, 157	.184
Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS)					
BIS	28.3 (3.4)	26.3 (3.6)	9.79	1, 157	.002
Fun Seeking	15.7 (2.8)	17.4 (2.3)	16.92	1, 157	<.001
Drive	15.3 (2.3)	15.8 (1.9)	2.66	1, 157	.105
Reward Responsiveness	20.9 (2.4)	21.3 (2.4)	0.78	1, 157	.378
Brief Fear of Negative Evaluation Scale	35.5 (8.1)	37.7 (10.3)	2.29	1, 157	.132

Note. Table reports means (SDs in parentheses) and comparison test statistics. Comparisons tested with ANOVA except where noted. Three participants did not report their ages; two did not report sex information. * Comparison tested with Chi-Squared.

2.2.2 Procedures

This study involved two testing sessions, separated by a week. In the first session, participants completed a series of questionnaires (the AQ and several personality measures; see Table 1) and a version of the reward sensitivity task, with either monetary or social reinforcement. In the second session, participants completed a second version of reward sensitivity task with the reinforcer to which they had not been exposed in session 1. Participants received monetary and social reinforcement in counterbalanced order. I used E-prime 2.0 to present the stimuli and collect responses (Psychology Software Tools, Pittsburgh, PA). Notably, this study used a double-blind design such that participants' status as high or low ASD trait participants remained unknown until the end of data collection.

2.2.2.1 Reward Sensitivity Task

The goal of this task was to measure reward sensitivity based on the development of reward-related response bias over the course of the task (Pizzagalli, Jahn, & O'Shea, 2005). The task instructed participants to earn as many rewards as possible by correctly identifying a line that appeared briefly on the screen as either "long" or "short". Participants identified the line using a key press (either the "1" key or the "2" key; key/line-length mappings were counterbalanced across subjects and sessions).

On each trial of the task, participants viewed a centrally presented fixation cross (1000ms duration). A frame (either a circle or a square, 18mm wide; for a participant seated .5 meter from the screen, this represents a visual angle of 2.062°) then appeared. After 500ms, a line appeared within the frame (either horizontally or vertically oriented).

The line remained visible for 100ms before disappearing. The frame was visible until participants made a response. Frame and line orientation were consistent for all the trials within a session, and participants experienced both frames and both line orientations across the two sessions in counterbalanced order. The long and short lines were similar in length (13mm as measured on screen [1.490°] and 12mm [1.375°] respectively), making the task relatively difficult.

Participants completed three blocks of 100 trials. Within each block, participants experienced 50 “short-” and 50 “long-line” trials, randomly ordered. The computer provided rewards on a pseudo-random selection of 40 correct trials. The task never gave participants feedback if they chose incorrectly. If participants made an incorrect response on a trial that was scheduled for reward, the reward was dispensed on the next trial of the same type that was not scheduled for reinforcement. This meant that most participants earned 100% of the reinforcements.

To encourage the development of a response bias, rewards were asymmetrically distributed such that correct responses to one of the lines received 30 of the 40 reinforcements whereas correct responses to the other line received only 10 of the reinforcements. If participants are sensitive to this asymmetric reward contingency, they should show the development of a response bias across blocks of the task (McCarthy & Davison, 1979; Pizzagalli, Jahn, & O’Shea, 2005). That is, they should be increasingly likely to choose the more richly rewarded stimulus on trials in which they were not certain which stimulus appeared. The computer counterbalanced the more richly rewarded line (long or short) across sessions.

When participants received reinforcement in the social reinforcement version of this task, they saw attractive genuinely smiling faces. Attractiveness was determined in an independent pilot study. These faces were visible for 2 seconds. During the non-social reinforcement version of the task, when they received reinforcement on a trial, they received a small monetary reinforcer (+3 cents). Previous research has shown that the average value of a genuine smile relative to a neutral face is worth approximately 2 to 3 cents (Heerey & Gilder, 2019), suggesting that both social and monetary rewards may be similar in value. Participants completed the social-reinforcement version of the task in one of the sessions and the non-social-reinforcement version of the task in the other session (in counterbalanced order). When participants completed the monetary version of the task, the experimenter paid them what they earned at the end of the study session.

2.2.3 Questionnaires

2.2.3.1 Autism-spectrum Quotient (AQ; Baron-Cohen, et al., 2001)

The Autism-spectrum Quotient is a fifty-item questionnaire that measures self-reported autism-related traits that focus on aspects of everyday life such as social interactions, communication ability and style and interpersonal skill (e.g., “I enjoy social chit-chat.”). I used it to assess self-reported autism-spectrum traits. Baron-Cohen and colleagues (2001) designed this questionnaire for a general adult population. The questionnaire uses a 4-point response scale (1 = definitely agree, 4 = definitely disagree). In the present sample, the AQ showed acceptable reliability across four of its subscales (Communication, $\alpha = .65$; Social, $\alpha = .60$; Attention to Detail, $\alpha = .62$; Attention Switching, $\alpha = .61$) with the imagination subscale showing poorer reliably than the others (Imagination, $\alpha = .55$). While these reliabilities are slightly lower than the original study, these reliabilities are consistent with other studies using North American and world-wide samples (Hoekstra, Bartels, Cath & Boomsma, 2008; Hurst, Mitchell, Kimbrel, Kwapil & Nelson-Gray, 2007; Wakabayashi, Baron-Cohen, Wheelwright, & Tojo, 2006). The AQ correlates with clinicians' assessments of ASD symptoms, supporting the validity of the AQ in terms of its ability to measure ASD traits (Baron-Cohen, Wheelwright, Skinner, Martin & Clubley, 2001).

2.2.3.2 Big-Five Inventory (BFI; John& Srivastava, 1999)

This 44-item questionnaire measures personality assuming a five-factor model. It assesses extraversion (e.g., "I see myself as someone who is sociable"), agreeableness (e.g., "I see myself as someone who is helpful and unselfish with others"), conscientiousness (e.g., "I see myself as someone who does a thorough job"), neuroticism (e.g., "I see myself as someone who is depressed, blue") and openness to experience (e.g., "I see myself as someone who is original, comes up with new ideas"). I used the BFI in the current study to assess whether aspects of the five-factor personality model such as extraversion differ across the ASD traits. Participants rated items on a 5-point Likert scale (1 = strongly agree; 5 = strongly disagree). In the present sample the BFI achieves high reliability across its 5 subscales (Extraversion, α = .84; Agreeableness, α = .78; Conscientiousness, α = .78; Neuroticism, α = .84; Openness, α = .78). Correlations with other established personality measures, such as the Neuroticism-Extraversion-Openness Personality Inventory provide support for the validity of BFI (John & Srivastava, 1999; Rammstedt & John, 2007).

2.2.3.3 Behavioral Inhibition/Behavioral Activation Scales (BIS/BAS, Carver & White, 1994)

This 24-item scale measures the degree to which people are motivated by rewards and punishments in the environment (e.g., "I go out of my way to get things I want," "Criticism or scolding hurts me quite a lot"). I used the BIS/BAS to assess whether there were any group differences between high ASD trait individuals and low ASD trait individuals. The scale's items are rated on a 5-point Likert scale (1 = very true for me; 5=very false for me). The BIS/BAS displays reasonable reliabilities across its 4 subscales (BIS, $\alpha = .73$; BAS Reward Responsiveness, $\alpha = .72$; BAS Drive, $\alpha = .65$; BAS Fun Seeking, $\alpha = .73$; Carver & White, 1994). Correlations with measures of anxiety, personality, and affect suggest that the scale is a valid measure of reward/punishment sensitivity (Campbell-Sills, Liverant & Brown, 2004; Carver & White, 1994; Jorm et al., 1998).

2.2.3.4 Brief Fear of Negative Evaluation Scale (BFNE, Leary, 1983)

The BFNE is a 12-item questionnaire that measures individuals' fear of negative social evaluation (e.g., "I am frequently afraid of other people noticing my shortcomings"). I used the BFNE to assess whether there were differences in fear of negative evaluation between high ASD trait individuals and low ASD trait individuals. The scale uses a 5-point Likert scale response (1=Not at all characteristic of me; 5=Extremely characteristic of me). The BFNE displays high reliability ($\alpha = .86$). Although it is not a direct measure of social anxiety, it measures a primary feature of social anxiety: concern about whether others hold negative evaluations of one's behavior (Leary, 1983; Rodebaugh et al., 2004). Given issues associated with social presentation in autism (e.g., Davis & Carter, 2014; Dawson et al., 2012; Sigman & Capps,1997; Volkmar, Cicchetti, Cohen & Bregman, 1992), I wanted to be able to statistically control for this potential confound.

2.2.4 Data Analysis

For the reward sensitivity task, I used a 'signal detection theory' approach to examine performance and the development of response bias over task blocks across the two reward types. I coded a response as a "hit" if participants correctly identified the more frequently rewarded (or "rich") stimulus on a given trial. A "false alarm" was coded if participants mistakenly identified an instance of the less frequently rewarded ("lean") stimulus as the rich one.

To compute d', I used the formula:

$$d' = Z_{HR} - Z_{FAR}$$

where *HR* represents a participant's hit-rate within a block of trials and *FAR* represents the false alarm rate. Z_{HR} is the z-transformed probability of correctly identifying the rich stimulus and Z_{FAR} is the z-transformed probability of incorrectly identifying the lean stimulus as the rich one. For response bias, I used the formula for "criterion" or *C* (see Macmillan & Creelman, 2004):

$$C = -1/2\,(Z_{HR} - Z_{FAR})$$

I calculated these measures on a block-by-block basis for each participant; excluding trials in which a participant's reaction time was shorter than 250ms or longer than 5000ms (see Pizzagalli, Jahn & O'Shea, 2005). I analyzed the resulting d' and C values using linear mixed-model analyses. The model used random effects for participants and used a restricted maximum likelihood estimation for the fixed effects of block (1, 2, 3), and reward-type (social, non-social). Block and reward-type were included as fixed within-subject measures, whereas AQ score ((<=17) versus high AQ score (>17)) was included as a between-subjects factor for the model. Importantly, the linear mixed-model analyses allowed me to examine the data in the context of the large amount of missing data across the sessions (i.e., 85 participants [53%] did not complete session 2 of the study).

2.3 Reward Sensitivity Results/Discussion

A linear mixed-model analysis of the line discrimination performance (d') showed that both groups performed similarly across the task (see Figure 2A). Exact statistical results appear in Table 2. Participants did not differ in the degree to which they were able to discriminate the long from the short line across the task and there were no significant interactions.

After establishing that participants did not differ in their ability to discriminate between the lines, I tested whether high- versus low-ASD trait participants differed in their sensitivity to social and non-social rewards by assessing the development of a response bias across blocks under different reward conditions. There were no significant effects of ASD traits or any significant interactions. However, there were significant main effects for feedback type, and a marginally significant main effect for block (see Figure 2B). Specifically, for feedback type, the linear contrast across feedback types was significant, suggesting that both groups developed a response bias that was stronger for monetary than social reinforcement conditions ($F(1,652) = 18.09$, p = <.001). As for block, participants showed evidence of greater response bias in block three compared to that in block one (F(1,652) = 6.15, *p* = .013). For exact results, see Table 2.

Overall, these results indicate that participants developed a stronger response bias to non-social rewards compared to social rewards, which replicates some previous findings (Chevallier et al., 2016; Lin et al., 2012). However, contrary to our hypothesis,

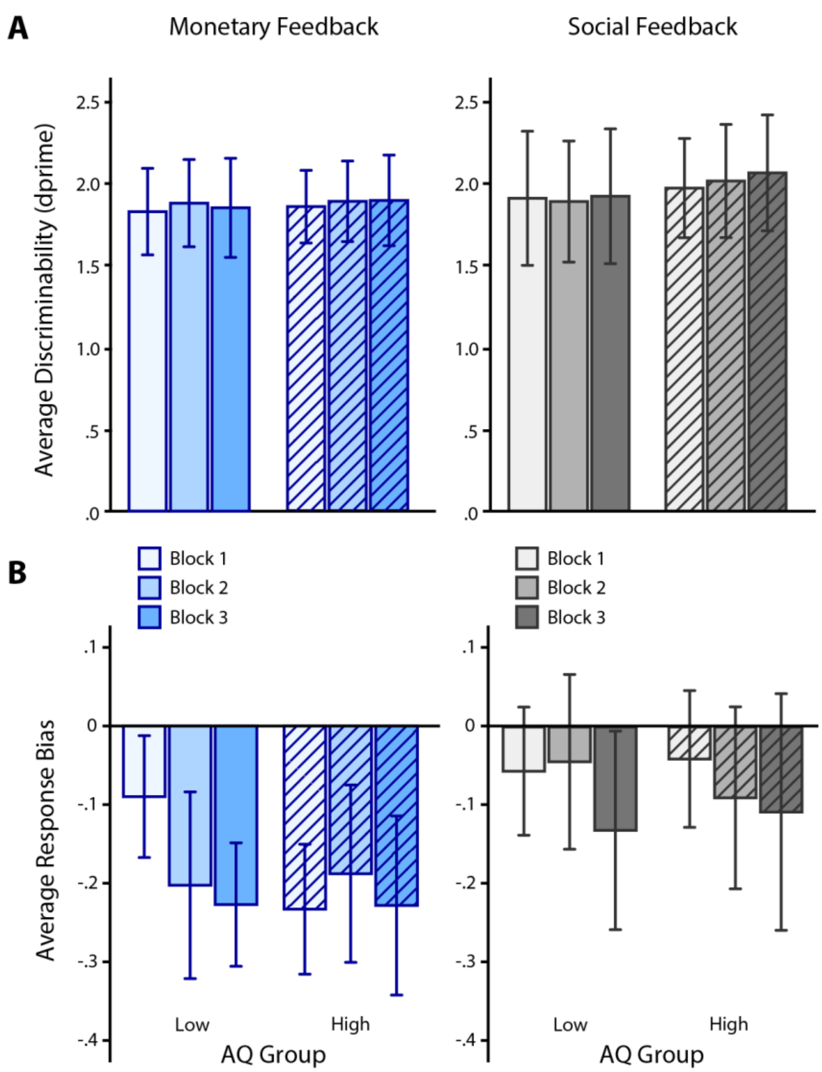

Figure 2. *Line Discrimination Task Results for high- and low-ASD trait participants.*
(A) Participant discriminability scores as a function of block and feedback type. (B) Response bias as a function of block and feedback type. Error bars show the 95% confidence interval.

there were no differences between high and low ASD-trait participants response biases in either reward condition. However, this study suffered from a couple limitations. In particular, only 47% of the sample received both monetary and social reinforcement conditions. This makes it difficult to compare across reinforcement types, the original goal of the task. In addition, because the dependency between autism-spectrum traits and reward sensitivity essentially relies on a correlation between these variables, it may be that even with the relatively large sample there was insufficient statistical power to detect these effects.

Table 2. *Effects of AQ, Feedback Type and Block on Participant Discriminability and Criterion*

Variable	df	*F*	*p*	*B*	*SE*
d'					
ASD	1, 625.2	0.69	.408	-0.15	0.23
Feedback Type	1, 625.2	0.63	.426	-0.15	0.26
Block	2, 401.3	0.06	.942	-0.09	0.24
ASD*Feedback	1, 625.2	0.29	.589	0.10	0.33
ASD*Block	2, 401.3	0.03	.972	0.06	0.29
Block*Feedback	2, 401.3	0.04	.964	0.09	0.34
ASD*Feedback*Block	2, 401.3	0.03	.971	-0.06	0.44
Criterion					
ASD	1, 583.9	3.01	.083	0.10	0.10
Feedback Type	1, 583.9	14.59	<.001	-0.06	0.09
Block	2, 387.5	2.98	.052	0.14	0.09
ASD*Feedback	1, 583.9	0.62	.431	-0.09	0.11
ASD*Block	2, 387.5	<0.01	.996	-0.10	0.11
Block*Feedback	2, 387.5	0.03	.969	-0.11	0.11
ASD*Feedback*Block	2, 387.5	1.88	.154	-0.08	0.16

Note. ASD = Autism-spectrum Disorder traits. Feedback Type refers to whether participants received social or non-social feedback during the task.

2.4 Smile Value

If the social motivation theory is correct, then individuals who report more autism-spectrum traits should value social rewards to a lesser degree. To test this hypothesis, I used a "smile valuation task" developed by our lab (e.g., Catalano, Heerey & Gold, 2018; Heerey & Gilder, 2019; Shore & Heerey, 2013) to assess how the subjective value of a smile relates to self-reported autism-spectrum traits. This task uses a choice method common in studies of economic utility (Von Neumann & Morgenstern, 1944) to examine how choice is shaped by social (smiles) and non-social (money) feedback. This project involved the secondary analysis of data from several samples collected between 2012 and 2019. Importantly, in this task, participants learn and respond to both monetary and social cues simultaneously. Rather than measuring simple ratings of different stimuli, participants' choices of one stimulus over another allow for the determination of social and nonsocial value (Catalano, Heerey & Gold, 2018; Heerey & Gilder, 2019).

2.5 Methods

2.5.1 Participants

Participants in this sample included a set of 509 individuals who completed a laboratory task designed to assess the degree to which participants value genuine and polite smiles, relative to neutral faces in monetary terms. Each of these participants had also completed the same self-report measure of autism-spectrum traits (the Autism Quotient Scale; see Table 3 for demographic characteristics). Participants completed these tasks in the context of a several of other studies designed to assess a number of different hypotheses. Even though AQ data were collected in each of these samples, relationships between task and autism-spectrum traits were never examined. This study represents the first systematic comparison of smile-valuation data and ASD traits amongst these individuals. This larger sample consists of six smaller samples of university students who completed the task in exchange for partial course credit and a small, performance-based monetary bonus. Across these studies, data were collected anonymously for initial research purposes. This secondary data analysis has therefore been granted a consent waiver by the NMREB at Western University.

Table 3. *Smile Valuation Task Demographic Information*

Participants	
n	509
Sex (Female:Male) *	347:161
Age in years	19.65 (3.09)
Autism-spectrum Quotient	
Total Score	17.16 (5.56)
Social Skills	2.17 (1.91)
Attention Shifting	4.78 (2.07)
Attention to Detail	5.43 (2.15)
Communication	2.39 (1.78)
Imagination	2.41 (1.60)
Range of Scores	4-40

Note. Table reports means (SDs in parentheses). One participant did not report their sex information.

2.5.2 Smile Valuation Task (Heerey & Gilder, 2019)

The Smile Valuation task participants completed is identical to the one used by Heerey and Gilder (2019). Briefly, the task has an exposure and a test phase. The reason for the exposure phase is to acquaint participants with a set of faces that differ in both social and monetary reward value. In this task phase, participants played a "guessing game" with a set of six opponents, each represented by a photograph of a face.

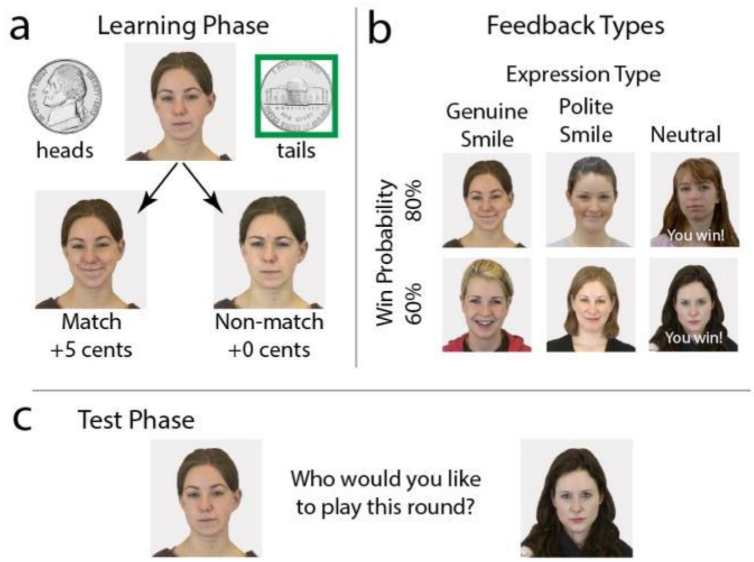

Figure 3. *Example of the smile value task with female stimuli.*
(A) Learning phase/exposure phase of the smile value task. Participants attempted to win money by choosing the same size of a virtual coin as an opponent. (B) Social and monetary feedback contingencies active during the exposure phase. (C) Test phase of the smile valuation task in which participants choose the best partner before continuing as in the exposure phase.

On each exposure-phase trial, participants viewed a single opponent, neutrally posted, in the center of the screen (Fig 3A). The images for this task were validated in a previous stimulus set (Heerey, 2014). All images showed an actor's head and shoulders. Actors' eye gaze was directed towards the viewer. Actors produced neutral expressions as well as polite and genuine smiles and frowns for the images used in this task. Polite smiles were created by asking the actors to produce them after seeing them demonstrated. To create genuine smiles, actors were asked to recall an experience in which they were happy, and to display this happiness as if with someone they knew. These expressions were recorded with a high-definition digital video camera. Static images were then clipped from the video sequences at peak expression. These images were validated in a subsequent study for genuineness, prototypicality and for the genuine and polite smiles, the degree to which participants were able to correctly classify them as genuine or polite. The images were in color.

Participants' ostensible goal in the present task was to attempt to win money by choosing the same side of a virtual coin as the opponent. When a participant's choice matched that of the opponent (i.e., a win trial), the opponent smiled genuinely (involving zygomaticus major and orbicularis oculi); smiled politely (zygomaticus major only); or remained in the neutral pose with text overlay indicating the win. Each win was worth \$0.03. On non-match trials, participants gained \$0.00. This feedback was indicated by the opponent frowning (previously smiling opponents), or a text overlay indicating a non-win (see Fig 3A).

In the exposure phase, task feedback did not depend on which side of the coin they chose. Instead, three of the opponents (randomly determined) provided 'match' feedback on 80% of trials while the remaining opponents provided 'match' feedback on 60% of trials. This was not known by participants. Additionally, two opponents (one 80% and one 60%) always presented genuine smiles on match trials; two presented polite smiles (one 80% and one 60%) and the others kept neutral poses (see Fig 3B). These reward values remained the same across all phases. Participants completed three blocks of 60 trials during the exposure phase, viewing opponents 10 times each per block in random order.

The test phase of the task allowed me to estimate, in monetary terms, how much participants valued polite and genuine smile feedback. In this phase of the task, participants chose which of two opponents they wanted to play on each trial. They were instructed to select the 'most valuable' opponents from amongst pairs of neutrally posed opponents presented side-by-side (see Fig 3C). After a participant chose an opponent, the trial continued in the same manner as the exposure phase. All fifteen possible opponent pairings manifested in random order, eight times each (120 test trials). Each opponent within a given pairing appeared as often in the left position as in the right position.

Opponent selection during the test phase served as the dependent variable in the task. Because participants chose between opponents in all 15 possible pairings, I was able to determine the degree to which money, genuine smiles, and polite smiles contributed to choice behavior. That is, if participants genuinely prefer one face to another in a given pairing, they will choose that face more often. If they have no preference for one face over another within a pairing, they will choose each face with about equal frequency. For example, if a participant prefers genuinely smiling to polite smiles, then that participant will select genuine smiling faces whenever they are asked to choose between a face that has a genuine smile and a face with a polite smile. This will be true even if the genuine smile has a lower chance of giving a monetary reward. Thus, this task measures the degree to which participants are willing to give up the chance to win money in favor of the chance to see genuine and polite smiles. Based on the relative differences between the monetary and social values of the faces in each pairing, and participants’ choice behavior, it is possible to identify how smiles shape participants choices relative to neutral faces, and how much high versus low monetary value affects their decisions.

To minimize the change that specific opponent/value pairings might affect results, each opponent's face appeared in each monetary/social value combination across participants with about equal frequency. Half of the participants viewed female opponents and half viewed male opponents, counterbalanced by participant gender.

2.5.3 Data Analysis

The choice participants made in this task allowed me to identify how opponent characteristics (money versus genuine and polite smiles) affected the participants' selection. I employed a logistic model to estimated how much money (lower value faces versus higher value faces) and smiles (genuine versus neutral; polite versus neutral) affected participants' decisions in the test phase of the smile-valuation task. The model predicted a participant's likelihood of choosing the left opponent, based on the relative differences between the opponents as follows:

$$P_{OpponentA}=\exp(\theta)/1+\exp(\theta)$$

In this function, $P_{Opponent\ A}$ is the probability of choosing the left opponent over the right opponent in a given pair of opponents (see Fig 3C). θ is estimated as:

$$\theta = \beta_{Money}X_{Money} + \beta_{Genuine}X_{Genuine} + \beta_{Polite}X_{Polite}$$

In this equation, βs are the unstandardized logistic regression weightings for each model component. The model coded X_{Money} as the difference between the left and right opponents' expected monetary values. I calculated expected values by taking the win value and multiplying it by its win probability (Sutton and Barto, 1998). For example, 3 cents multiplied by either an 80% or a 60% chance of winning. Based on these calculations, X_{Money} received a value of '.6' if the left opponent was better than the right, '-.6' if the right opponent was better, and '0' if they were equal. $X_{Genuine}$ coded whether the opponents smiled genuinely (relative to neutral faces). It was set equal to 1 if the left opponent smiled genuinely and the right was neutral, -1 if the expressions were reversed and 0 if both or neither of the opponents smiled genuinely. X_{Polite} coded for polite smiles in similar fashion to $X_{Genuine}$ (see Heerey & Gilder, 2019). The model estimated regression weights using an iteratively re-weighted least squares algorithm using a purpose written scripts for MATLAB (r2020a). The model calculated the maximum likelihood estimates for each value in the equation (Daubechies, DeVore, Fornasier & Güntürk, 2010). Participants' data were fit individually to obtain values for both the utility of genuine smiles, polite smiles and money on a participant-by-participant basis. The current study examines the correlation between the unstandardized regression coefficients and self-reported ASD traits. Additionally, I examined which type of feedback were valued by participants (i.e. greater than 0). For this analysis I categorized participants as either high (AQ > 17) or low ($AQ \leq 17$) ASD traits.

2.6 Smile Valuation Results/Discussion

First, I ran an analysis to see if participants valued the feedback they received, to ensure the task worked. Both high and low ASD trait participants placed value significantly above zero on both the money, genuine smile, while only high ASD trait participants placed value significantly above zero on polite smiles (see Figure 4A and Table 4 for more details).

Contrary to predictions made under the social motivation theory of autism, results showed no relation between ASD traits and the utility of either smiles (genuine: r(509) = .-.042, p = .344; polite: r (509) = -.001, p =.991) or money (r(509) = -.058, p = .194; see Figure 4). Thus, in this large participant sample there was no relationship between ASD-related traits and the utility of either social or monetary value. These data suggest that individual differences in the degree to which participants value genuine and polite smiles are unlikely to relate to self-reported traits of autism.

Table 4. *Results of One-sample t-test of values for Money, Genuine Smiles and Polite Smiles*

Variable	df	t	Sig
Low ASD Traits			
Money	272	11.23	<.001
Genuine Smile	272	7.08	<.001
Polite Smile	272	1.60	.110
High ASD Traits			
Money	234	9.50	<.001
Genuine Smile	234	5.67	<.001
Polite Smile	234	2.69	.008

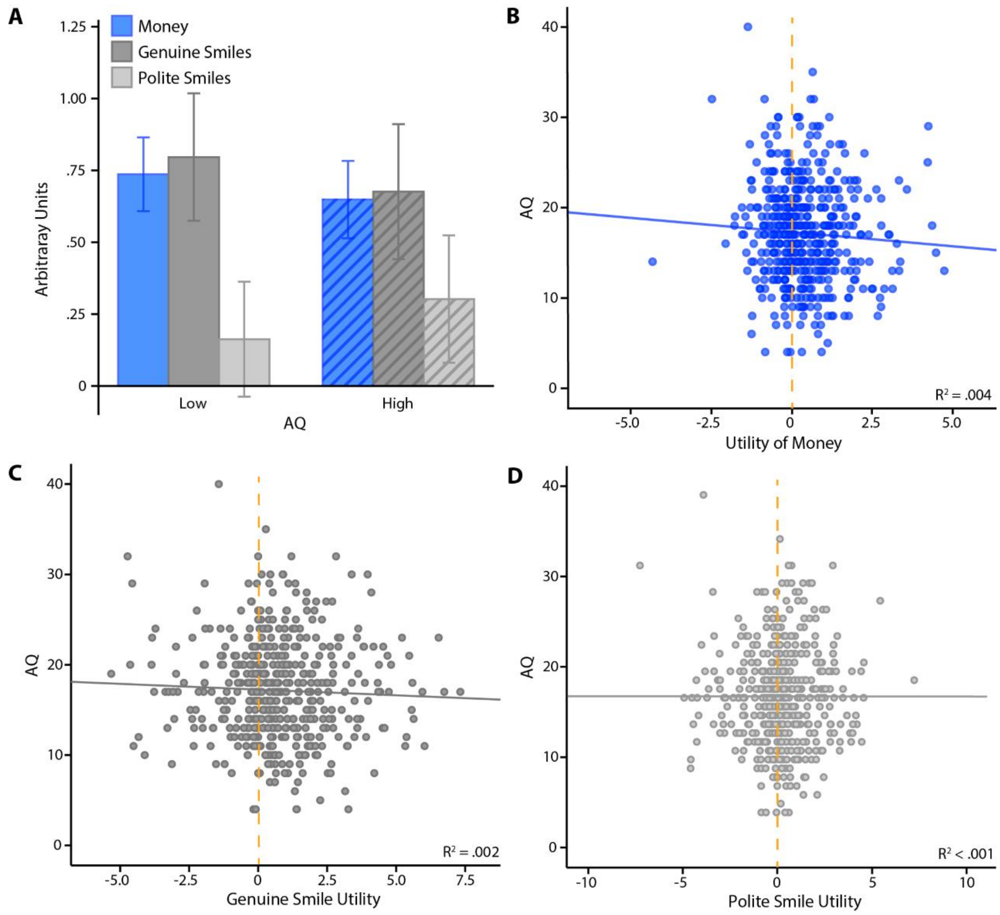

Figure 4. *Smile Valuation Task Correlations.*
(A) Feedback Values (B) AQ score correlation with Monetary feedback, (C) AQ score correlation with Genuine Smiles feedback, (D) AQ score correlation with Polite Smiles feedback

Note: AQ = Autism-spectrum Quotient. Arbitrary Units (*β)* = Unstandardized logistic regression weightings for each feedback type.

2.7 General Discussion

Overall, I found no relationship between task performance and ASD-related traits (as measured by the AQ) on either the line discrimination task or the smile valuation task. These results are contrary to the social motivation hypothesis (Chevallier et al., 2012; Clements et al., 2018). Thus, autism-spectrum traits do not appear to affect the degree to which participants develop a response bias under social reinforcement nor do these traits relate to estimates of smile utility within the general population samples. Taken together, none of the findings in this chapter support a potential motivational mechanism that would explain the behavioral differences seen across the autism spectrum in individuals both with and without diagnoses.

However, this the work in this chapter also has some limitations. For example, attrition was an issue in the study in which the line discrimination task was completed. That is, a large number of participants only completed one session out of two, making it challenging to directly compare social and non-social feedback within person. Additionally, the group that completed the line discrimination task displayed several unexpected group differences. For example, those who scored higher on the AQ reported a higher level of extraversion compared to those who reported fewer ASD traits. This is unusual response pattern, compared to what is typically found (Austin, 2005). This may impact the generalizability of these results.

I now shift focus to potential cognitive mechanisms that might explain ASD-traits in Chapter 3, which investigates the weak central coherence hypothesis.

3 Testing the Weak Central Coherence Hypothesis of Autism

Due to, in part, the conceptualizations of Frith (2003), research in the area of ASD has advanced several theories based upon the idea that people with ASD show a bias toward local, rather than global processing, the most prominent being the weak central coherence hypothesis (Happe, 2005; Iarocci & McDonald, 2006; Morgan, Maybery & Durkin, 2003; Muth, Hönekopp & Falter, 2014; Simmons, Robertson, McKay, Toal, McAleer & Pollick, 2009; Van der Hallen et al., 2015). This hypothesis has found widespread support in the literature as research shows that people with ASD and those who report higher levels of autism-related traits appear to have a bias toward "local" versus "global" processing. Specifically, individuals with more ASD-traits or with ASD diagnoses perform better compared to controls on tasks that require attention to fine detail (Bolis & Schilbach 2018; Burghoorn et al., 2018; Crewther & Crewther, 2014; Frith & Happé, 1994; Grinter et al., 2009; Happé & Frith, 2006; López et al., 2004; Morgan et al., 2003; Van der Hallen et al., 2018).

In the current chapter I examine individual differences in the tendency to prefer global versus local processing in individuals who self-report autism-spectrum traits. I use the Leuven embedded figures task (L-EFT; de-Wit, et al., 2017) to explore this question. In the L-EFT, participants search for an abstract "target" shape embedded within a larger abstract image as quickly as possible. Importantly, this style of task has been widely used in the literature and evidence regularly shows support for the weak central coherence hypothesis (Cribb, Olaithe, Di Lorenzo, Dunlop & Maybery, 2016; Muth et al., 2014).

3.1 Methods

3.1.1 Participants

I recruited 207 participants (see Table 4 for demographic characteristics and group comparisons) from the Western Psychology Participant Pool (SONA; N=132) along with a mixed community sample recruited using advertisements and word of mouth (N=75). They participated in exchange for partial course credit or a monetary payment of $15. The Western University Nonmedical Ethics Board approved all study procedures and participants documented their informed consent prior to participating.

I removed 3 participants' L-EFT performance data from the analysis for inattentive responding using the same strategy as in previous research using the L-EFT (de-Wit, Huygelier, Van der Hallen, Chamberlain & Wagemans, 2017). Specifically, I defined fast errors as inaccurate trials in which the respondent answered within 1.5s. I used a cut-off of >15% fast errors. None of the remaining participants performed below chance level (<.33). Additionally, I removed one participant from all analyses for invariant questionnaire responding.

For this analysis I classified participants as either low or high AQ based on a median split. I classified participants who scored 19 or lower as "low AQ participants" and those who scored above 19 as "high AQ participants." Refer to Table 5 for demographic information. For demographic information based upon social competency groupings (as measured by the MSCS), refer to appendix C.

Table 5. *Demographic Information for L-EFT task*

AQ Group	High AQ (AQ > 19)	Low AQ (AQ ≤ 19)	*F*	*df*	*p*
n	97	109			
Score Range	20-39	6-19			
Sex (Female:Male) *	69:28	89:19	3.68	1,204	.055
Age in years	20.0 (4.1)	21.3 (8.8)	1.87	1,204	.173
Autism-spectrum Quotient					
Total Score	25.4 (3.8)	15.0 (3.1)	466.35	1,205	<.001
Social Skills	5.3 (2.2)	1.8 (1.4)	186.30	1,205	<.001
Attention Shifting	6.69 (1.5)	4.2 (1.8)	109.59	1,205	<.001
Attention to Detail	6.1 (2.2)	5.6 (2.1)	3.23	1,205	.074
Communication	4.0 (1.9)	1.5 (1.3)	132.67	1,205	<.001
Imagination	3.4 (1.8)	1.9 (1.3)	44.25	1,205	<.001
Big Five Inventory					
Extraversion	35.5 (8.6)	26.3 (9.0)	56.44	1,205	<.001
Agreeableness	28.7 (8.0)	23.7 (6.6)	24.47	1,205	<.001
Conscientiousness	30.5 (7.4)	27.9 (8.3)	5.70	1,205	.018
Neuroticism	26.9 (9.0)	33.3 (8.5)	27.41	1,205	<.001
Openness	34.9 (8.6)	31.2 (8.4)	9.96	1,205	.002
Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS)					
BIS	23.1 (3.3)	21.8 (3.4)	8.72	1,205	.004
Fun Seeking	11.2 (2.2)	12.9 (2.2)	30.72	1,205	<.001
Drive	10.8 (2.2)	11.5 (2.3)	4.48	1,205	.036
Reward Responsiveness	17.7 (1.6)	17.9 (1.8)	0.27	1,205	.604
Multidimensional Self Concept Scale (MSCS)					
Social Motivation	35.2 (3.3)	35.7 (5.3)	0.73	1,205	.394
Demonstrating Empathetic Concern	38.5 (5.2)	41.3 (5.6)	18.85	1,205	<.001
Nonverbal Sending Skills	36.8 (3.9)	37.8 (6.6)	1.68	1,205	.197
Social Inferencing	36.7 (3.3)	36.9 (5.5)	0.19	1,205	.661
Social Knowledge	45.1 (5.3)	47.8 (6.4)	10.53	1,205	<.001
Verbal Conversation Skills	32.3 (5.1)	31.80 (7.8)	0.31	1,205	.576
Emotion Regulation	33.6 (4.8)	32.3 (7.4)	2.35	1,205	.127
Reading the Mind In the Eyes Task (RMET)					
Total Score	24.6 (4.8)	26.9 (4.0)	13.45	1,205	<.001
Letter Number Sequence Task (LNS)					
Total Score	14.9 (4.9)	15.1 (3.9)	0.10	1,198	.751

Note. Table reports means (SDs in parentheses) and comparison test statistics. Comparisons tested with ANOVA except where noted. 1 participant did not report their age; 1 did not report sex information. *Comparison tested with Chi-Squared.

3.1.2 Procedures

The study occurred in a single session of about 90 minutes. Participants completed a series of questionnaires (the AQ and several other measures; see Table 4. for a complete description), a computer-administered letter-number sequencing task as a proxy measure of IQ, as well as the Leuven Embedded Figures Task (L-EFT). They also completed a short video-recorded social interaction (See Chapter 5.2.2 for more details). Windows computers running E-prime 2.0 Professional (Psychology Software Tools; Sharpsburg, PA) presented the computerized tasks and collected responses.

3.1.2.1 Leuven Embedded Figures Task (L-EFT; de-Wit, et al., 2017)

The L-EFT (de-Wit, et al., 2017) consisted of 64 trials, presented in a random order, in which participants searched for an abstract "target" shape embedded within a larger abstract image. The L-EFT uses a matching-to-sample paradigm in which participants viewed a target image centered in the top half of the computer screen. Below the target, there were three "context" images, one of which contained the embedded target image (Figure 5). Participants chose which context contained the target as quickly and accurately as possible by clicking on the image using the computer mouse. Stimuli were continually visible until participants gave a correct response (i.e., there was no time limit for responding). If participants responded incorrectly, the computer provided visual feedback on their performance (a red frame appeared around the incorrect choice) and they were prompted to give a new response until they provided the correct answer. This helped to ensure that participants understood the task and did not simply click through the trials (see de-Wit, et al., 2017). Trials on which the first response was an error were excluded from analysis. This procedure is consistent with previous research and helped to ensure that participants actively engaged in the task. The computer presented the three embedding contexts at three fixed locations on the lower half of the screen and the "correct" position was randomly determined on each trial. There were easy medium and hard trials that varied in image difficulty according to a computerized algorithm (de-Wit, et al., 2017). This algorithm defined image complexity as the number of ‘distractor lines’ the image contained. These lines were lines that continued from the target image itself into the surrounding context or vice versa. The more distractor lines the image contained, the more difficult it was (0, 1, 2 or 3 lines).

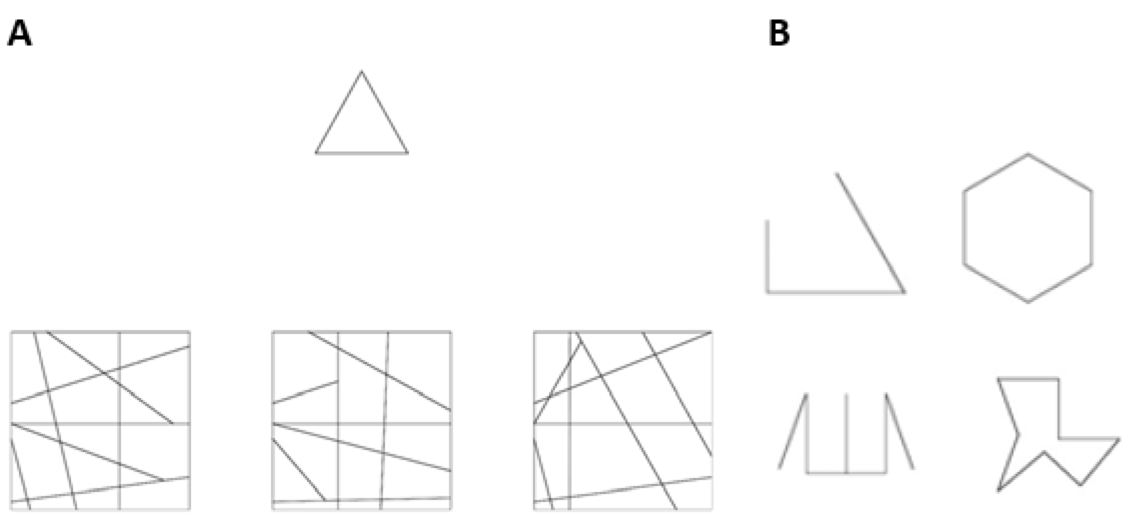

Figure 5. *Example of a L-EFT Trial.*
A) An example of a trial with 2 ‘distractor lines’. B) Example target shapes.

3.1.2.2 Letter Number Sequencing Task (LNS; Wechsler, 1997)

The LNS, a component of the Wechsler Adult Intelligence Inventory (Wechsler, 1997), was used as a proxy intelligence measure and to determine whether L-EFT performance was associated with working memory (see de-Wit, et al., 2017). This version of the task used a computerized form developed by Mielicki, Koppel, Valencia & Wiley, (2018). In this version of the task, participants viewed scrambled letter-number sequences, one character at a time, on the computer screen and responded using the keyboard. Sequences were presented in a fixed order, similar to that in face-to-face administrations. The task included three sequences at each of eight difficulty levels (2-digit, 3-digit, 4-digit, etc.) for a total of 24 trials. Participants completed all trials of the task regardless of performance. Each trial began with a fixation cross for 1000ms, followed by a 300ms blank screen. The characters of the sequence then appeared one-at-a time. Each of the characters in the sequence remained visible for 1000ms, separated by a blank screen (300ms duration) between characters. After of the final character of the trial, participants were instructed to type the numbers first in ascending order followed by the letters in alphabetical order. They pressed <ENTER> to register their response.

3.1.3 Questionnaires

Participants completed the Autism-spectrum Quotient, the Big-Five Inventory and the Behavioral Inhibition/Behavioral Activation Scales to measure autism traits, personality and reward seeking/punishment avoidance as in Chapter 2. They also completed the Multidimensional Social Competence Scale and the Reading the Mind in the Eyes Test (see below).

3.1.3.1 Multidimensional Social Competence Scale (MSCS; Yager, & Iarocci, 2013)

The MSCS is a 77-item questionnaire that measures self-reported social competency traits that focus on aspects of social skills such as social motivation (e.g., “I enjoy meeting new people.”), social inferencing (e.g., “I can tell when people are joking.”), demonstrating empathic concern (e.g. “I am sensitive to the feelings and concerns of others.”), social knowledge (e.g. “I understand what makes a true friend.”), verbal conversation skills (e.g. “I give other people a chance to speak during conversations.”), nonverbal conversation skills (e.g., “I look at people in the eye when talking to them.”), and emotional regulation (e.g. “I get over setbacks or disappointments quickly.”). I used it to assess self-reported autism-spectrum traits in conjunction with the AQ. Trevisan and colleagues (2018) designed the measure for an adult general population. The questionnaire uses a 5-point response scale (1 = not true or almost never true, 5 = very true or almost always true). In the present sample the MSCS displayed excellent reliability overall (α = .912) with good reliability across it subscales (social motivation, α = .848; social inferencing, α = .746; demonstrating empathic concern, α = .811; social knowledge, α = .823; verbal conversation skills, α = .818; nonverbal conversation skills, α = .777; and emotional regulation α = .749.

3.1.3.2 Reading the Mind In the Eyes Task (RMIET, Baron-Cohen, Wheelwright, Hill, Raste & Plumb, 2001)

This 36-item task measures the degree to which people can identify emotion in images of people’s eyes. I used to RMIET to assess whether there were any group differences between high AQ and low AQ scorers on emotion perception, an important social skill thought to be related to social ability. For each trial of the task, the computer displayed a single photo of a person's eyes with four possible 1-word descriptions for the affect depicted in the photo. Participants selected the word that they believed best described the emotion displayed on the face. The average performance of RMIET in non-clinical samples ranges from 26.0 (4.2) items correct to 28.6 (3.2) (Baron-Cohen et al., 2001; Ferguson, F. J., & Austin, 2010). The current sample achieved consistent results.

3.1.4 Data Analysis

I examined how individuals endorsing high versus low levels of ASD traits differed in their local and global processing ability using both overall response times, as well as total errors made. To analyze these dependent variables, I conducted several analyses using standard mixed-model ANOVAs (SPSS 24.0; IBM Corp, 2016). As a general performance check, my first analysis investigated task difficulty (low, medium and high), which was defined as the number of lines of the target shape that continued into the surrounding context (de Wit et al., 2017) as a fixed, within-subjects measure, with AQ Group (Low AQ (<=19) versus High AQ score (>19)) included as a between-subjects factor for the model. I expected the dependent variables of response time and errors to increase across difficulty levels but to do so to a greater degree for those in the Low AQ group, who are thought to have reduced local processing skill compared to high-AQ individuals.

3.2 Results

3.2.1 L-EFT RT (AQ)

In this series of analyses, I examined whether ASD traits affected the response times on the L-EFT. Additionally, I investigated whether ASD traits interacted with any specific design feature (e.g. target image difficulty, target image complexity, shape openness or shape symmetry). For each of these analyses I conducted a 2 x 4 mixed-model ANOVA with AQ Group (Low versus High) as the between-subjects variable (image difficulty, image complexity, shape openness, shape symmetry) as the within-subjects variables and RT (ms) as the dependent variable. General task results were similar to previous findings such that there were significant effects of target difficulty, complexity, and symmetry on reaction times. Specifically, the more challenging it was to find the target shape within the image (more lines from the shape continuing into the surrounding context, the more lines that the shape had, if the shape was asymmetrical), the slower participants completed the trial (for exact results, see Table 6).

Interestingly, I found no significant effects of ASD-traits and no significant interactions, such that ASD-traits appear to have no impact on participants' response times, regardless of the features of the target shape (see Table 6). As results were not consistent with previous studies, I also conducted an exploratory analysis examining only the most difficult or most complex image results (i.e., target images that had 4 lines continue into the surrounding context and those target images that consisted of 8 lines). Again, I found no significant ASD-related differences impacting response time for the most difficult or complex images ($p > .05$).

Table 6. *Effects of AQ, Difficulty, Shape, and Symmetry on Participant Response Time and Errors*

Variable	df	*F*	*p*	η_p^2
Response Time				
AQ	1,202	0.70	.402	.003
Difficulty	3,202	228.77	<.001	.532
Complexity	3,202	70.76	<.001	.260
Shape Openness	1,202	0.03	.855	<.001
Symmetry	1,202	4.68	.032	.023
AQ*Difficulty	1,202	1.27	.275	.006
AQ*Complexity	1,202	1.85	.137	.009
AQ*Shape	1,202	0.43	.515	.002
AQ*Symmetry	1,202	2.60	.109	.013
Errors				
AQ	1,202	3.30	.071	.016
Difficulty	3,603	369.28	<.001	.648
Complexity	3,603	19.26	<.001	.087
Shape Openness	1,202	5.12	.025	.025
Symmetry	1,202	56.25	<.001	.219
AQ*Difficulty	3,603	1.60	.205	.008
AQ*Complexity	3,603	1.02	.381	.005
AQ*Shape	1,202	0.41	.521	.002
AQ*Symmetry	1,202	0.35	.554	.002

Note. AQ = Autism-spectrum Quotient. Feedback Type refers to whether participants received social or non-social feedback during the task.

3.2.2 L-EFT Total Errors (AQ)

In this series of analyses, I examined whether ASD traits affected the number of errors people made on the L-EFT, as well as whether those traits interacted with any specific design feature as above (e.g., target image difficulty, target image complexity, shape openness or shape symmetry). As with the response time analyses, there were no significant effects for ASD-traits and no significant interactions (results appear in Table

5). Thus, ASD-traits did not appear to affect the number of errors participants made in the task.

As with response time, I also conducted an exploratory analysis looking at only the most difficult or most complex image results (i.e., target images that had 4 lines continue into the surrounding context and those target images that consisted of 8 lines) to see whether ASD traits affected errors to the most difficult shapes where previous results suggest that those with high levels of ASD-related traits should outperform those endorsing fewer traits (Burghoorn, et al., 2018; Jolliffe & Baron-Cohen, 1997; Grinter et al., 2009; Happé & Frith, 2006; Van der Hallen, et al., 2018). In these very specific cases for high and low ASD trait individuals I found that there was a significant difference in error rates ($F(1, 202) = 4.694$, $p = .031$), such that individuals endorsing high levels of ASD traits made fewer errors compared to individuals endorsing fewer ASD traits (1.84 vs 2.33 errors made). Thus, a bias toward local processing appeared to enhance performance at the most difficult task level for those with high levels of ASD traits. However, due to the exploratory nature of this analysis, these results must be interpreted with caution.

3.2.3 L-EFT Performance (MSCS)

In addition to analyzing the results with the AQ, I also analyzed the results using a median split on the MSCS. As with the AQ, I examined both response times and errors as the dependent variables in the analyses. Generally, these exploratory analyses showed similar patterns as those of the AQ for both response time and number of errors. However, the interaction between MSCS group and image complexity for response time, did reach statistical threshold. Specifically, as the image became more complex, response

Table 7. *Effects of MSCS, Difficulty, Shape, and Symmetry on Participant Response Time and Error Rate*

Variable	df	*F*	*p*	η_p^2
Response Time				
MSCS	1,202	0.21	.647	.001
Difficulty	3,202	225.23	<.001	.528
Complexity	3,202	69.35	<.001	.257
Shape Openness	1,202	0.01	.921	<.001
Symmetry	1,202	4.00	.047	.020
MSCS*Difficulty	1,202	0.65	.585	.003
MSCS*Complexity	1,202	3.20	.043	.016
MSCS*Shape	1,202	0.78	.377	.004
MSCS*Symmetry	1,202	1.69	.195	.008
Error Rate				
MSCS	1,202	0.04	.844	<.001
Difficulty	3,603	368.95	<.001	.647
Complexity	3,603	19.23	<.001	.087
Shape Openness	1,202	5.36	.022	.026
Symmetry	1,202	57.24	<.001	.223
MSCS*Difficulty	3,603	0.26	.752	.001
MSCS*Complexity	3,603	0.77	.606	.003
MSCS*Shape	1,202	0.15	.704	.001
MSCS*Symmetry	1,202	0.54	.543	.002

Note. MSCS = Multidimensional Social Competency Scale. Feedback Type refers to whether participants received social or non-social feedback during the task.

times slowed for both high and low social competency individuals, but response times slowed significantly more for low social competency individuals compared to the high social competency individuals (See Table 7 for results). Note that because the directionality of the MSCS is opposite that of the AQ (i.e. it tests social competency instead of social deficits with higher scores denoting better social competency), then this result is contrary to predictions that the low social-competency group should perform better than the high social-competency group. No other differences emerged and due to the exploratory nature of this analysis, results should be interpreted with caution.

3.3 Discussion

As in previous chapters, I failed to find that differences in ASD traits related to task performance operationalized in terms of response times or error rates. Thus, the only significant modulator of performance in this sample of participants appeared to be task difficulty. That is, task performance declined as the task became harder, as previous research shows (de Wit et al., 2017, Van der Hallen et al., 2018), however, task difficulty-based performance decrements did not show the predicted interactions with ASD traits.

This study has a couple of important limitations. First, like other samples I collected in this work, individuals who reported more autism-traits also reported being more extraverted compared to those endorsing fewer traits, which may make them unusual or atypical of individuals who experience higher levels of ASD traits. Second, conclusions for this chapter are based on a single task. There are a variety of other tasks that also measure central coherence and it might be that some of these other tasks would have captured group differences (Conson et al., 2013; Deruelle et al., 2006; Grinter et al., 2009; Jolliffe & Baron-Cohen, 1999; Pellicano et al., 2006; Snowling & Frith, 1989). Ideally, I would have replicated this finding with a second task also measuring central coherence, However, Covid-19 interfered with any additional data collection I might have completed.

Overall, none of the findings in this chapter show strong support for the idea that processing biases explain the social behavioral differences seen across the autism spectrum. I now turn to probabilistic learning mechanisms to investigate whether previous results based on the thinking behind probabilistic learning models replicate in large general population samples.

4 Testing the Probabilistic Learning Hypotheses of Autism

Probabilistic models of human learning, including reinforcement learning models, have long been used to explain how humans learn from, adapt to, and make decisions based on contingencies within the natural environment (Bayer & Glimcher, 2005; Chamberlain et al., 2016; Cools, Clark, Owen & Robbins, 2002; Dayan & Jyu, 2003; Kriegeskorte, 2015; Friston, 2003; Mathys, Daunizeau, Friston & Stephan, 2011; Niv & Montague, 2009; O'reilly, 2001; Seymour, Daw, Roiser, Dayan & Dolan, 2012). More recently, such models been implemented in the emerging field of computational psychiatry, being applied to schizophrenia (Averbeck, Evans, Chouhan, Bristow & Shergill, 2011; Waltz & Gold, 2007; Waltz, Frank, Wiecki & Gold, 2011), addiction (Baker, Stockwell & Holroyd, 2013; Clark & Robbins, 2002; Izquierdo & Jentsch, 2012; Myers et al., 2016), and more recently, autism spectrum disorder as well (Aberg et al., 2016; D’Cruz et al., 2013; Oaksford & Chater, 2001; Robic et al., 2016; Sevgi et al., 2020; Solomon et al., 2011). Broadly, these models suggest that many aspects of human behavior can be understood in terms of how humans learn from, interact with and attempt to control outcomes within their environments (Chater et al., 2006; Griffiths, 2009; Meyniel, Schlunegger & Dehaene, 2015; Oaksford & Chater, 2001). These outcomes (e.g., rewards and punishments) vary in the degree to which they are predictably associated with actions and therefore learnable, both within and across environmental contexts (Meyniel et al., 2015; Pietschmann, Endrass, Czerwon & Kathmann, 2011; Koch et al., 2008; Schenk, Lech & Suchan, 2017).

In the domain of autism, recent literature has found that individuals with autism-spectrum traits appear to have particular difficulty appropriately responding when rewards and punishments are probabilistic versus deterministic (Aberg et al., 2016; Robic et al., 2016; Sevgi et al., 2020; Solomon et al., 2011). This work suggests that these difficulties occur both when 'environmental inputs' (stimuli) are probabilistic in nature and when 'environmental output' (feedback) is probabilistic (Sevgi et al., 2020; Solomon et al., 2011). Additionally, a formal autism spectrum diagnosis is not necessary for these effects to appear, as similar findings regularly occur across both clinical and non-clinical populations (e.g., Bolis & Schilbach 2018; Karvelis, Seitz, Lawrie & Seriès, 2018; Pellicano & Burr, 2012; Sevgi et al., 2020). This suggests that the ability to learn from probabilistic contingencies within the environment may give rise to at least some autism-spectrum symptoms and traits.

The work in this chapter investigates how self-reported autism-spectrum traits (as measured by the Autism-spectrum Quotient [AQ]; Baron-Cohen et al., 2001) are linked to individuals' ability to learn from social and non-social stimuli and rewards that are either deterministically or probabilistically reinforced, in the context of either social or non-social stimuli/feedback. Some of the data in this chapter was collected in conjunction with studies in Chapters 2 and 5.

4.1 Learning from Social and Nonsocial Feedback

4.2 Methods

4.2.1 Participants

These data were collected in the same study as reported in Chapter 2 (see Table 1 for details). Participants completed a probabilistic selection task (Solomon et al., 2011) alongside the questionnaires and asymmetric reinforcement task presented in Chapter 2. I removed seven participants' data from the task due to inattentive responding. I defined a participant as being inattentive on the task if their responses were either faster than 250ms or slower than 5000ms on over 30% of trials (e.g., Jain, Bansal, Kumar & Singh, 2015; Welford, 1980).

4.2.2 Procedures

In addition to the tasks and questionnaires outlined in Chapter 2 sections 2.2.2. and 2.2.3, participants completed a Probabilistic Selection Task (Frank, Seeberger & O'Reilly, 2004) under social and nonsocial reinforcement.

4.2.2.1 Probabilistic Selection Task

Participants completed a modified version of a Probabilistic Selection task (Frank et al., 2004; Solomon et al., 2011). The goal of this task was to measure participants' ability to learn probabilistically reinforced response contingencies from both social and non-social feedback conditions. Participants received social feedback in one session and monetary (non-social) feedback in another session, with session order counterbalanced across participants.

The task consisted of a training phase followed by a test phase. I informed participants that on each trial of the training phase, they would see a pair of images appear side-by-side on the screen (see Figure 6). The same two images would always occur in a pair. I instructed participants to try to choose the "correct" image in each of the pairings. They were also told that one of the stimuli in any given paring was "more likely" to be correct than the other and that they should use the feedback they received, to select the stimulus that was more likely to be correct. Participants were aware that they would sometimes receive invalid feedback after choosing the typically correct stimulus.

The training phase of the task contained four possible stimulus pairings (8 images total) “AB,” “CD,” “EF,” and “GH.” The stimulus pairs within the task each had different reward contingencies. In the AB pair, the “A” object was reinforced at a rate of 80%, meaning that on 80% of trials (randomly determined), the A object was reinforced and on 20% of trials, the B object was reinforced. Thus, participants received invalid feedback on 20% of trials. The CD pair was reinforced at 70/30 (C was reinforced on 70% of trials). The EF pair had a 60/40 reinforcement rate and was therefore the most difficult to learn. For the first two presentations with each pairing, the computer ensured that the feedback was valid to reduce the possibility that early invalid reinforcement did not ultimately determine task performance (for an explanation of this issue, see Baker, Stockwell, and Holroyd, (2013)). In addition, to examine learning from deterministic feedback, the training phase included a 4th stimulus pairing (the GH pair) that was deterministically reinforced (100/0), such that “correct” selections were always reinforced. This pairing was not included in the original task (Frank, et al., 2004; Solomon et al., 2011).

On each trial, participants viewed a fixation cross (500ms duration), followed by a pair of stimuli (ordinary object images such as a bird or an apple), presented side-by-side on the computer screen. The computer randomly assigned images to pairs. In each task block, the computer presented 20 trials of each pairing in random order, with each stimulus appearing on the left side of the display on 50% of trials. Participants then selected one of the two images in the pair by pressing a key corresponding to the location of the stimulus they wished to select (the images remained on the screen until they made a selection). After participants selected a stimulus, a frame appeared (for 500ms) around the stimulus they chose, to highlight their selection. Participants then received feedback (1000ms) that was either monetary or social in nature. For social feedback, participants saw an attractive, genuinely smiling face for correct choices and a frowning face for incorrect choices. For non-social feedback, they viewed a text display showing either, “Correct! +3 cents” or “Incorrect! +0 cents”. I counterbalanced feedback type across study sessions and participants viewed a new selection of object stimuli in each session (see Figure 6).

Participants completed up to four blocks of 80 trials in the training phase. To ensure that participants learned the criteria but were not over-trained, those who guessed the correct stimulus on 65%, 60% and 40% for the AB, CD, and EF trials respectively proceeded to the test phase at the end of the block in which they achieved these scores, as in previous research (e.g., Frank et al., 2004; Solomon et al., 2011). Participants who failed to meet these criteria by the final training block also moved onto the test phase, however their test-phase data were excluded from analyses (Total Removed Sessions: n=23; Social = 16; High AQ = 8). These criteria ensured that participants had achieved similar levels of learning when they entered the test phase.

During the test phase of the task, participants viewed familiar and novel pairings of the “A” through “F” stimuli from the training phase (they viewed all possible pairings of the AB, CD and EF pairs; e.g., AB, AC, AD, AE, AF; BC, BD, BE, BF, etc.) and continued to attempt to choose the “best” stimulus in each pairing. In this phase, participants viewed each of the possible stimulus pairings 6 times in random order. They received no reinforcement during this task phase. The GH stimuli were excluded from the test phase, as these stimuli were not present in the original task (Frank et al., 2004).

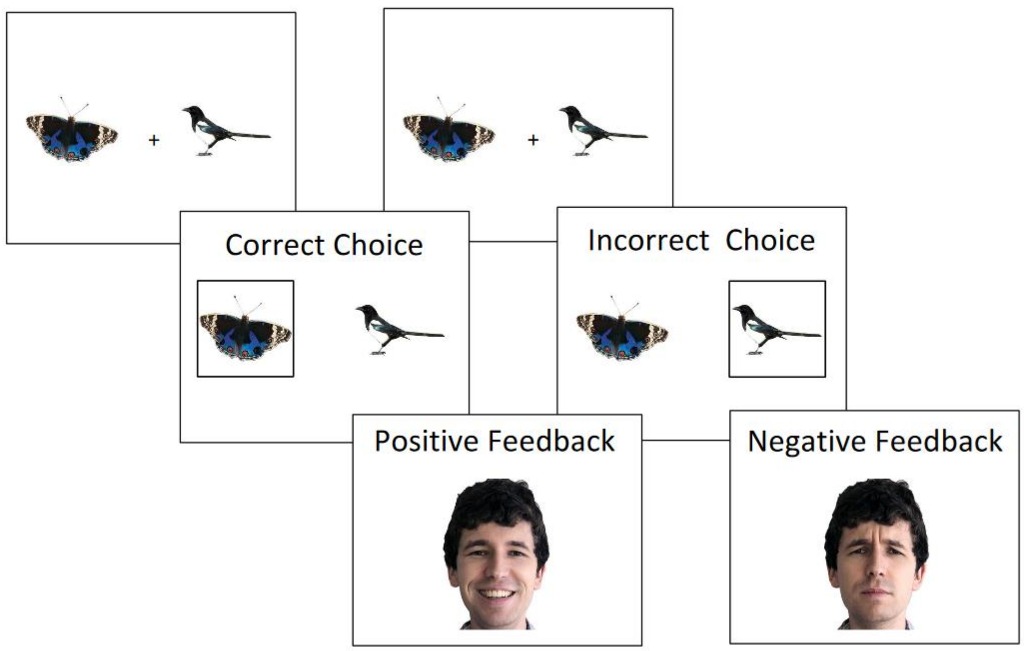

Figure 6. *Probabilistic Selection Task.*

Example trials for the probabilistic selection task training phase. Subjects viewed four stimulus pairs that provided valid feedback with different frequency (100% valid reinforcement, 80% valid reinforcement, 70% valid reinforcement, and 60% valid reinforcement). The same stimuli always occurred in a pair and pairs appeared in random order. Participants chose which of the two stimuli was most likely to be correct. Positive feedback was either a monetary reward (non-social) or a smiling face (social), whereas negative feedback consisted of a monetary reward of 0 cents or a frowning face. In the test phase of the task, participants saw all possible stimulus pairings and received no feedback.

4.2.3 Data Analysis

The probabilistic selection task examined a series of research questions. To examine participant overall performance, I used ‘proportion correct’ of the task trials. To examine how quickly participants learned the different pairings and how this related to reward type, I calculated a measure of learning speed for each of the different stimulus pairings. This measure, “trials to criterion”, was calculated as the number of trials participants needed to make five consecutive selections of the most frequently rewarded image in a given pair (e.g., choosing the 80% stimulus five times in a row in the 80%/20% stimulus pair). To analyze proportion correct and trials to criterion I used a linear mixed-model in SPSS 24.0 (IBM Corp, 2016) to account for missing data (recall that only 47% of participants completed both sessions; see Chapter 2 for details). Participants were entered as a random effect in the model and I used a restricted maximum likelihood estimation for the fixed effects of pairs (AB, CD, EF, GH), and reward-type (social, non-social). Pairs and reward-type were included as fixed within-subject measures, whereas AQ group (low AQ [<=17] versus high AQ [>17]) was included as a between-subjects factor in the model.

Research additionally suggests that individuals with ASD may have difficulty exploiting rewarded stimuli under probabilistic response contingencies (Solomon et al., 2011; Zeeland et al., 2010). I therefore investigated “win–stay” behavior (the frequency of choosing the same stimulus again on the next trial after receiving a reward for it on the previous) and “lose–shift” behavior (shifting to the alternative stimulus immediately following non-reward). As in previous studies (Solomon et al., 2011), I coded win–stay behavior as the percentage of trials following positive feedback in which the participants chose the same stimulus, and lose–shift behavior as the percentage of trials following negative feedback in which participants avoided choosing the same stimulus. I analyzed ‘win-stay’ and ‘lose-shift’ behavior using similar linear mixed-model analyses as above.

I also ran an exploratory analysis on the test phase data to see whether participants differed in their ability to learn from novel stimuli pairings. I investigated how many correct choices participants made in the test phase defined as a participant choosing the most rewarding stimulus in the test pairings. In the model participants were entered as random effects and I used a restricted maximum likelihood estimation for the fixed effect for reward-type (social, non-social). Reward-type (social, non-social) was included as fixed within-subject measures, whereas ASD traits (low AQ [<=17] versus high AQ [>17]) was included as a fixed between-subjects factor.

4.3 Results/Discussion

4.3.1 Probabilistic Selection Task: Learning Phase Results

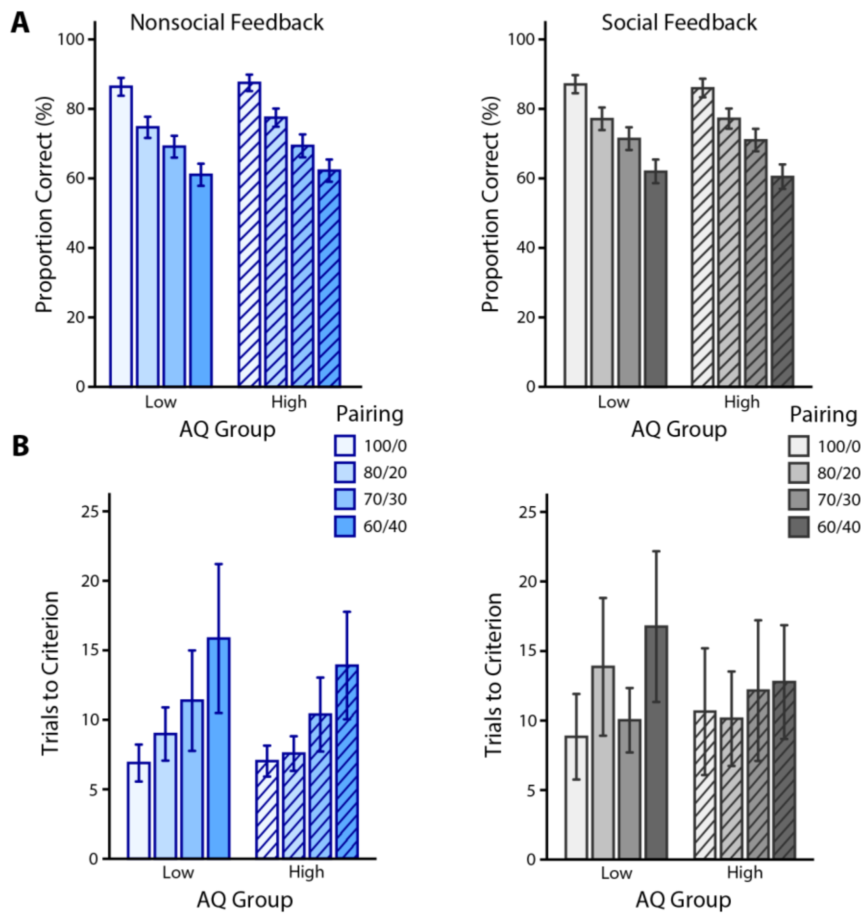

Figure 7. *Probabilistic Selection Task Learning Block.*
(A) Proportion Correct as a function of pairing, ASD traits and feedback. (B) Trials to Criterion as a function of pairing, ASD traits and feedback. Error bars represent 95% confidence intervals.

In the learning phase of this task, my goal was to assess how individuals differed in their ability to learn from social and non-social feedback. To examine this, I examined the ‘trials to criterion’ measure in the linear mixed-model described above. I found no significant effects for feedback type or ASD traits but I did find a significant main effect

Table 8. *Exact ANOVA Results for the Effects of Behavior Type, AQ, Feedback Type on Participant Performance ‘Trials to Criterion’ and Win-Stay, Lose-Shift Behavior*

Variable	df	*F*	*p*	*B*	*SE*
Proportion Correct					
Pairing	3, 381.4	44.06	<.001	0.11	0.03
AQ	1, 671.3	0.34	.562	0.03	0.04
Feedback Type	1, 671.3	1.05	.305	0.05	0.03
AQ*Feedback	1, 671.3	0.12	.729	-0.01	0.04
Pairing*AQ	3, 381.4	1.47	.224	-0.05	0.05
Pairing*Feedback	3, 381.4	1.19	.312	-0.04	0.04
Pairing*AQ*Feedback	3, 381.4	0.24	.867	0.03	0.06
‘Trials to Criterion’					
Pairing	3, 381.4	7.50	<.001	2.11	3.07
AQ	1, 671.3	1.21	.272	-1.78	2.71
Feedback Type	1, 671.3	3.22	.073	3.56	2.02
AQ*Feedback	1, 671.3	<0.01	.951	1.64	2.84
Pairing*AQ	3, 381.4	1.39	.247	5.73	4.32
Pairing*Feedback	3, 381.4	1.08	.359	4.67	3.90
Pairing*AQ*Feedback	3, 381.4	0.59	.620	-3.64	5.49
Win-Stay Behavior					
ASD Traits	1, 222.9	4.10	.044	-2.65	1.04
Feedback Type	1, 222.9	1.23	.269	-0.48	1.08
ASD Traits*Feedback	1, 222.9	3.23	.074	2.50	1.39
Lose-Shift Behavior					
ASD Traits	1, 222.9	0.02	.902	-0.31	0.87
Feedback Type	1, 222.9	3.74	.054	-1.37	0.91
ASD Traits*Feedback	1, 222.9	0.17	.170	0.48	1.17

Note. AQ is the Autism-spectrum Quotient. Feedback Type refers to whether participants received social or non-social feedback during the task. Pairing refers to the proportion of valid feedback within a given pairing (i.e., 100/0, 80/20, 70/30, or 60/40).

for the proportion of valid feedback within a pairing. As anticipated, the greater the proportion of invalid feedback, the longer it took participants to learn the correct image in the pairing ($F(1,452) = 8.87$, $p = .003$). There were no significant interactions (see Figure 7B and Table 8 for results). These findings suggest that the more often people receive invalid feedback, the more difficult it is for them to learn from that feedback but that learning rates do not depend on ASD-traits. When analyzing proportion correct, the findings were the same with only a main effect of pairing existing (See Figure 7A).

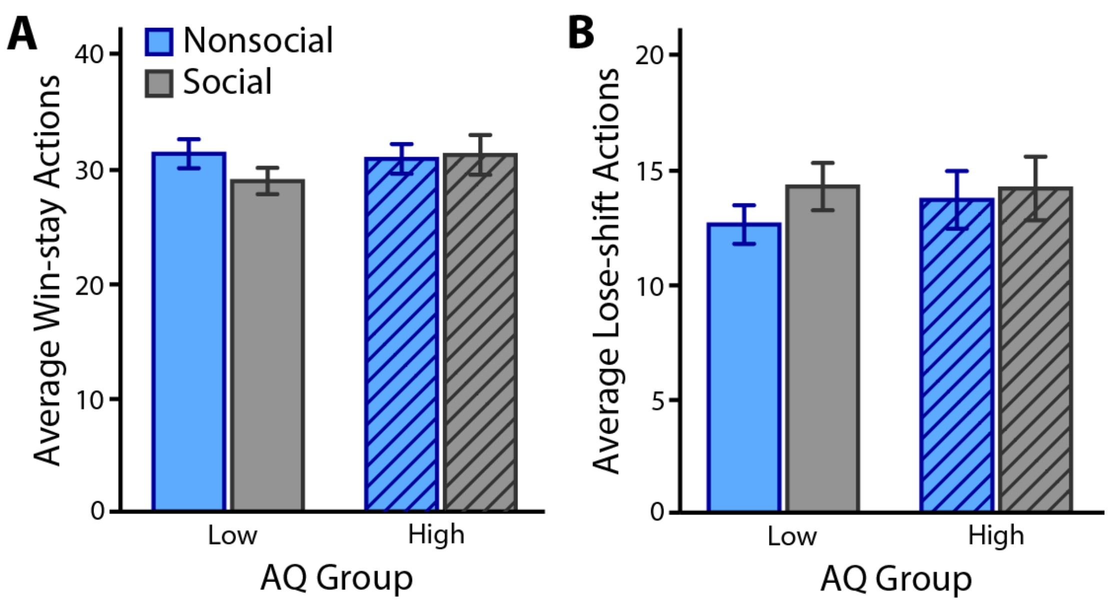

Figure 8. *Probabilistic Selection Task Learning Block Behavior.*
(A) Proportion of Win-Stay behavior as a pairing, AQ and feedback. (B) Proportion of Lose-shift behavior as a pairing, AQ and feedback. Error bars represent 95% confidence intervals.

I also tested participants' win-stay and lose-shift behavior, as the literature suggests that this may be an important reason for why those with high AQ scores perform more poorly in tasks such as this (Solomon et al., 2011). For win-stay behavior, analysis suggested that individuals with greater ASD traits engaged in more win-stay actions compared to those with fewer ASD traits (see Table 8 for Linear mixed-model results). There were no significant effects when using lose-shift behavior as the dependent variable (See Figure 8).

4.3.2 Probabilistic Selection Task: Test Phase

In the test phase, my goal was an exploratory analysis to see whether participants differed in their ability to select the "best" stimulus in novel stimuli pairings. As above, I conducted a linear mixed-model analysis using total correct choices as the dependent variable. I found no significant effects for feedback type or ASD traits. Additionally, the interaction was non-significant (see Table 9 for results).

Table 9. *Exact ANOVA Results for the effects of AQ and Feedback Type on Performance*

Variable	df	*F*	*p*	*B*	*SE*
Performance (Total Score)					
ASD Traits	1, 210.7	0.203	.653	-0.83	1.72
Feedback Type	1, 210.7	0.836	.362	0.85	1.91
ASD Traits*Feedback	1, 210.7	0.050	.824	0.55	2.46

Note. ASD traits as measured by the Autism-spectrum Quotient. Feedback Type refers to whether participants received social or non-social feedback during the task.

4.3.3 Discussion

Overall, and in contrast to previous reports using a similar task (Solomon et al., 2015, Solomon et al., 2011), there were no significant differences between AQ groups when it came to task performance in the probabilistic selection task. In addition, reinforcement condition did not seem to affect results differently across the groups.

There are several possible reasons for my failure to replicate previous results in this study (see Baker et al., 2013; Fritz & Scherndl, 2014; Schutte et al., 2017 Simonsohn, 2015). These have to do with modifications made to the original task that might have interfered with the replication. First, unlike the original task, my version of the task ensured that participants received valid feedback on the first two presentations of each stimulus pairing when participants were initially sampling the environment. I opted for this because of work suggesting that early invalid feedback may cause participants to learn the “wrong” selection, which they must then unlearn, thereby changing the nature of the task (see Buekers, & Magill, 1995; Ernst, & Steinhauser, 2015; Muller-Gass, Duncan, Tavakoli & Campbell, 2019). There is some evidence for this idea in the data. Specifically, the present participants performed substantially better than did participants in previous research (see Solomon et al., 2011). For example, over a third of participants in prior versions of this task were excluded from the test phase for poor learning performance, suggesting the possibility that early invalid feedback may change the nature of the task. Second, I used photos of recognizable everyday objects as stimuli in this task, rather than the Hiragana characters used previously. Evidence suggests that some Hiragana characters are easier to remember than others meaning that the random assignment of characters to pairing may impact learning independent of the more important aspects of the task itself (Baker et al., 2013; Schutte et al., 2017). Together, these modifications may have affected my ability to replicate previous findings. In addition, choice behavior in the test phase of task has been shown to have poor test-re-test reliability (Baker et al., 2013), calling into question what exactly this phase of the task measures.

4.4 Probabilistic Learning: Replication

To follow up on these results and correct confounds associated with the Probabilistic Selection task, I ran a conceptual replication of the task, with several key changes. My predictions were identical to those above.

4.5 Methods

4.5.1 Participants

I recruited 298 participants from the Western Psychology Participant Pool to complete the study in exchange for partial course credit. I removed 13 participants from the analysis due inattentive responding in the task leaving a total of 285. I defined a participant as being inattentive to the task if on over 30% of the trials their response was faster than 250ms or slower than 5000ms. Using a median split approach, I classified participants who scored 18 or lower as low AQ participants and those who scored above 18 as high AQ participants (see Table 10 for demographic characteristics and group comparisons). The Western University Nonmedical Ethics Board approved all study procedures and participants documented their informed consent prior to participating.

Table 10. *Demographic Information for Probabilistic Selection Task replication*

AQ Group	High AQ (AQ > 18)	Low AQ (AQ ≤ 18)	*F*	df	*p*
n	147	138			
Score Range	19-37	7-18			
Sex (Female:Male) *	112:35	101:36	0.23	1,279	.631
Age in years	18.9 (3.1)	18.4 (0.9)	3.27	1,280	.071
Autism-spectrum Quotient					
Total Score	23.4 (3.6)	14.2 (2.7)	604.92	1,283	<.001
Social Skills	4.0 (2.2)	1.4 (1.3)	144.67	1,283	<.001
Attention Shifting	6.3 (1.6)	4.17 (1.7)	118.37	1,283	<.001
Attention to Detail	6.1 (2.1)	5.0 (2.0)	23.31	1,283	<.001
Communication	3.8 (1.9)	1.5 (1.2)	151.51	1,283	<.001
Imagination	3.2 (1.7)	2.1 (1.5)	30.73	1,283	<.001
Big Five Inventory					
Extraversion	31.4 (8.6)	38.8 (7.3)	61.54	1, 283	<.001
Agreeableness	46.1 (7.5)	49.1 (7.2)	11.95	1,283	.001
Conscientiousness	42.4 (7.9)	43.1 (8.0)	0.42	1,283	.519
Neuroticism	35.4 (8.5)	30.6 (9.0)	21.31	1,283	<.001
Openness	46.4 (7.7)	47.8 (8.7)	2.19	1,283	.140
Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS)					
BIS	23.0 (3.4)	21.3 (3.9)	16.60	1,283	<.001
Fun Seeking	11.8 (2.2)	12.7 (2.4)	9.67	1,283	.002
Drive	11.2 (2.3)	11.4 (2.1)	0.52	1,283	.471
Reward Responsiveness	18.0 (1.9)	17.9 (1.9)	0.37	1,283	.545

Note. Table reports means (SDs in parentheses) and comparison test statistics. Comparisons tested with ANOVA except where noted. Three participants did not report their ages; one did not report sex information.
*Comparison tested with Chi-Squared.

4.5.2 Procedures

The study occurred in a single session. Participants completed a series of questionnaires (the AQ and several personality measures; see Table 3) and a new version of the Probabilistic Selection Task. In this version, participants experienced task blocks with both social and non-social reinforcement, in counterbalanced order, allowing for direct comparison across these feedback types. Windows computers running E-prime 2.0 (Psychology Software Tools, Pittsburgh, PA) presented the stimuli and collected responses.

This version of the task included several methodological changes. First, to make the social feedback directly relevant to the experimental context, participants received social feedback from the experimenter. That is, the computer showed them photos of their experimenter's face, either genuinely smiling for positive feedback or frowning for negative feedback. In order to enhance the salience of this feedback, the experimenter informed participants that in one of the study conditions they would see feedback from "me," (the experimenter) that would indicate performance. Experimenters also demonstrated each expression for participants and noted its meaning in the task. Pilot testing suggested that this manipulation carried some real social value. In addition, I also changed the non-social feedback to simple green ticks or red crosses depending on whether participants got the answer correct or incorrect, respectively. This is more consistent with the previous research (Frank et al., 2004) and eliminated the monetary feedback component.

Second, to address the possibility that I had made the task too easy by guaranteeing that participants received valid feedback during the first two trials, I eliminated this contingency and simply randomized feedback order. This change is consistent with the methodology of the original study (Frank et al., 2004). All participants completed two blocks of 80 trials each, under both social and non-social reinforcement conditions, thereby equalizing the number of trials across participants. In order to reduce experimental fatigue, I eliminated the test phase because of associated methodological and interpretational concerns (Baker et al., 2013). The stimuli remained as above, including the same images, randomly assigned to pairings and feedback types.

4.5.3 Questionnaires

With the exception of the BFNE, which did not suggest differences in social concerns across the groups, the questionnaires remained exactly the same as those reported in the previous study. They were: The Autism-spectrum Quotient, the Big-Five Inventory and the Behavioral Inhibition/Behavioral Activation Scales.

4.5.4 Data Analysis

Here, because all participants completed the task under both feedback conditions, I examined task hypotheses with a standard mixed-model ANOVA (SPSS 24.0; IBM Corp, 2016). Similar to the previous analysis, proportion correct and trials to criterion (defined as above) were the dependent variables in the first two analyses. Pairs (100/0, 80/20, 70/30, 60/40), and reward-type (social, non-social) were included as fixed within-subjects measures, whereas ASD grouping (AQ score low (<=18) versus high (>18)) was included as a between-subjects factor in the models. Additional mixed-model ANOVAs also examined “win–stay” and “lose–shift” behavior as it related to reinforcement type (social/non-social; within-subjects) and ASD group (High/Low; between subjects).

4.6 Probabilistic Selection Task Results

With respect to overall task performance, using proportion correct, results were consistent with the previous analysis and besides the expected main effect of pairing, no significant effects or interactions were found (See Figure 9A). With respect to the rate at

Table 11. *Exact mixed-ANOVA Results for the Effects of Behavior Type, AQ, Feedback Type on Participant Performance 'Trials to Criterion' and Win-Stay, Lose-Shift Behavior Usage*

Variable	df	*F*	*p*	η_p^2
Proportion Correct				
Pairing	3,283	284.28	<.001	.501
AQ	1,283	0.26	.607	.001
Feedback Type	1,283	0.71	.399	.003
AQ*Feedback	1,283	1.08	.299	.004
Pairing*AQ	3,283	0.37	.778	.001
Pairing*Feedback	3,283	1.44	.231	.005
Pairing*AQ*Feedback	3,283	0.38	.765	.001
'Trials to Criterion'				
Pairing	3,283	87.20	<.001	.236
AQ	1,283	0.79	.375	.003
Feedback Type	1,283	0.04	.848	<.001
AQ*Feedback	1,283	1.51	.220	.005
Pairing*AQ	3,283	1.25	.291	.004
Pairing*Feedback	3,283	0.92	.964	<.001
Pairing*AQ*Feedback	3,283	2.30	.086	.008
Win-Stay Behavior				
AQ	1,283	0.29	.592	.001
Feedback Type	1,283	1.28	.258	.005
AQ*Feedback	1,283	0.21	.648	.001
Lose-Shift Behavior				
AQ	1,283	0.06	.814	<.001
Feedback Type	1,283	7.57	.006	.026
AQ*Feedback	1,283	1.82	.179	.006

Note. AQ is the Autism-spectrum Quotient. Feedback Type refers to whether participants received social or non-social feedback during the task. Pairing refers to the proportion of valid feedback within a given pairing (i.e., 100/0, 80/20, 70/30, or 60/40).

which participants learned, using 'trials to criterion' as the dependent measure, results were consistent with the previous analysis. There were no significant effects for AQ or feedback type. As above, I found a significant main effect for pairing (see Figure 9B for exact results) such that it took longer for participants to learn the correct response as the proportion of invalid feedback increased (F(3, 258) = 225.02, *p* = <.001). The null main effects of feedback and AQ-level suggest that individuals, regardless of self-reported AQ and feedback type, acquire probabilistic contingencies at similar rates (see Table 11 for

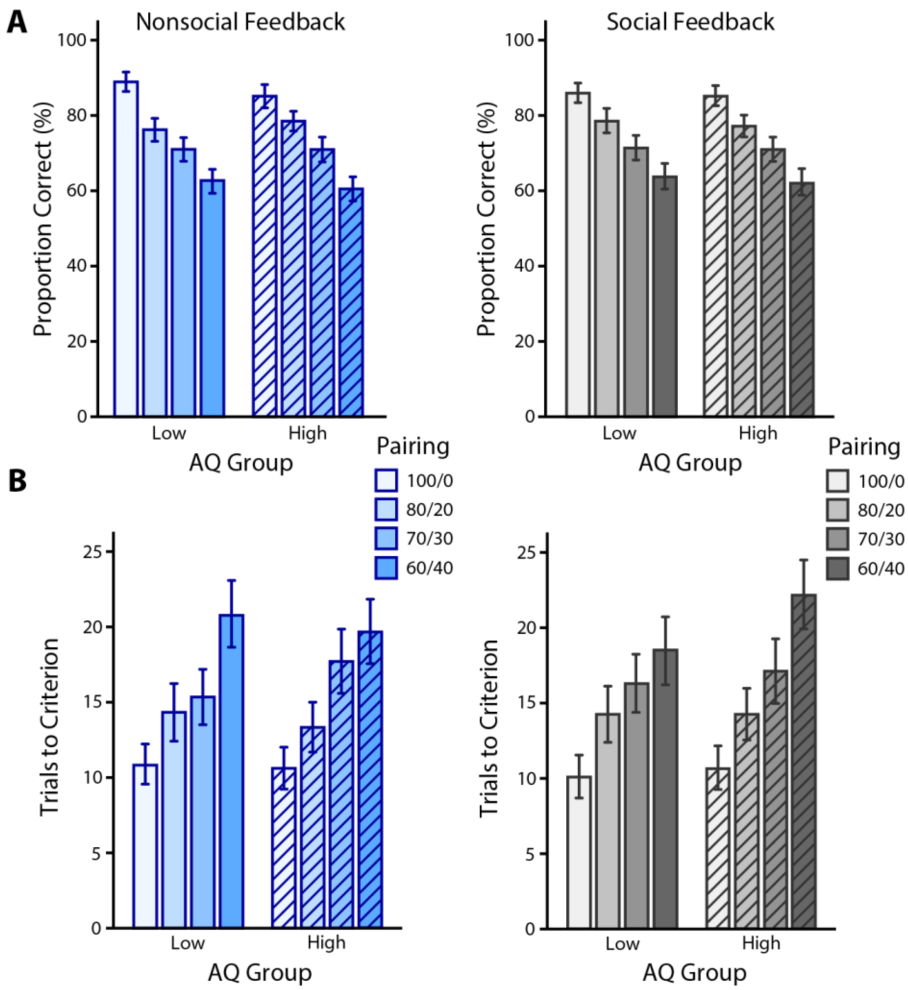

Figure 9. *Probabilistic Selection Task.*
(A) Proportion Correct as a function of pairing, AQ and feedback. (B) Trials to Criterion as a function of pairing, AQ and feedback. Error bars represent 95% confidence intervals.

exact results).

Analysis of participants' win-stay behavior revealed no significant effects for AQ or feedback type, suggesting that there were no differences associated with this type of task decision-making (see Figure 10A). However, for 'lose-shift' behavior there was a significant effect for feedback type, such that participants made more lose-shift behaviors during non-social feedback compared to social feedback (see Figure 10B). The null findings for ASD traits suggest that individuals, regardless of self-reported ASD traits engage in similar win-stay, lose-shift behavior patterns when learning probabilistic contingencies (see Table 11 results).

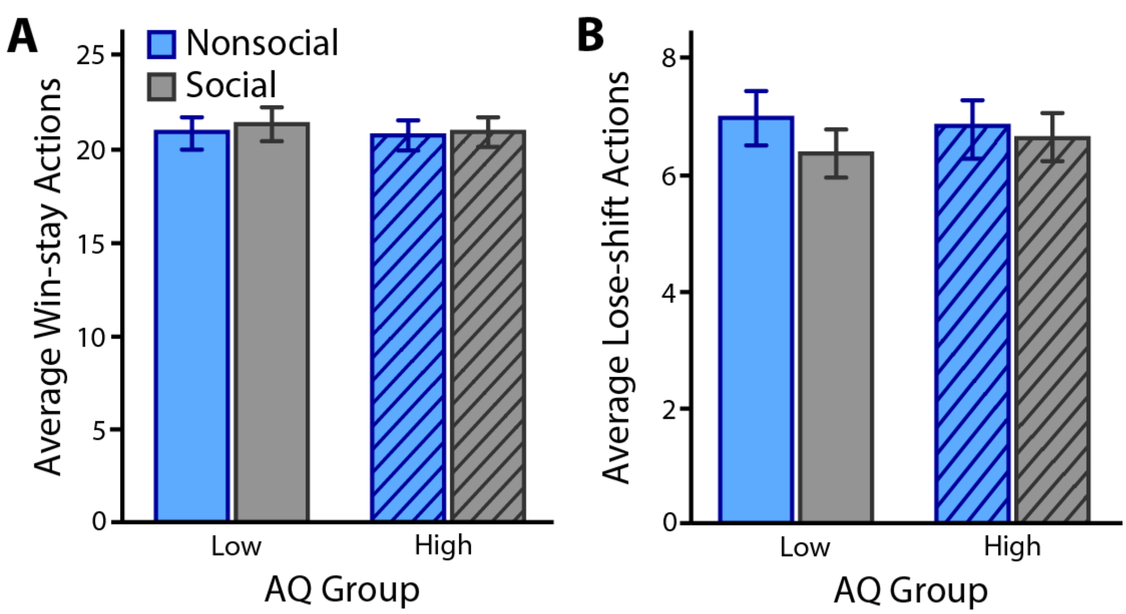

Figure 10. *Probabilistic Selection Task Learning Block Behavior.*
(A) Proportion of Win-Stay behavior as a pairing, AQ and feedback. (B) Proportion of Lose-shift behavior as a pairing, AQ and feedback. Error bars represent 95% confidence intervals.

4.7 Discussion

Overall, I found no relationship between performance and participants' self-reported AQ levels in the probabilistic selection task. This replicated result is contrary to the predictions proponents of the probabilistic learning hypotheses make as well as previous research findings (Solomon et al., 2011). However, these null results are consistent across our larger and certainly reasonably powered samples and suggest that self-reported ASD traits are not predictive of performance on the probabilistic selection task, regardless of feedback type. Thus, learning differences do not seem to be associated with self-reported traits of autism, unlike previous reports (Baker et al., 2013; Schutte et al., 2017; Solomon et al., 2011).

4.8 Learning from the Environment

Despite the fact that learning from social versus non-social feedback did not seem to differentially affect performance across ASD-trait groups, it is also the case that success in face-to-face interactions involves using social cues to predict others' behavior (Fawcett, & Liszkowski, 2012; Levesque & Kenny, 1993; Sacheli, Aglioti & Candidi, 2015; Sauppé & Mutlu, 2014). This is the question to which I now turn. Here, I assess the degree to which participants learn to use social and non-social cues as they make choice decisions. Importantly, as in real social interactions, the cues that served to predict the "correct" behavior on a trial-to-trial basis had contingencies that changed over the course of the task. Thus, participants in this study needed to integrate information from multiple cues, each of which had different likelihoods of providing "correct" advice that changed over time. I was interested in the degree to which variation in the reliability of natural reward contingencies related to participants' ability to integrate and make use of different types of environmental stimuli (e.g., social vs. non-social stimuli). To assess this, I used an associative learning task (Behrens, Hunt, Woolrich & Rushworth 2008; Sevgi et al., 2020) that included both social and non-social stimuli. This task was used for two reasons. First, it allowed a test of the prediction that if probabilistic learning is associated with autism-spectrum traits, participants reporting high levels of autism-spectrum traits should perform worse under conditions of volatility (i.e., periods in which reinforcement contingencies fluctuate in the degree to which they are reliable) and perhaps to a greater degree when the stimuli are social. Second, a critique of the previous probabilistic selection task might be that the task is too easy to learn. This task is more challenging because it requires participants to learn from two contingencies that change over the course of the task. If low task difficulty was obscuring autism-trait group differences, this more challenging task should correct that problem.

4.9 Methods

4.9.1 Participants

I recruited participants (N=195) from the Western University psychology participant pool (SONA) to complete the study in exchange for partial course credit and a small monetary bonus. I classified participants as either low or high AQ based on a median split. Participants who scored 17 or lower were the low ASD trait participants and those who scored above 17 were high ASD trait participants (see Table 12 for demographic information). The Western University Nonmedical Ethics Board approved

Table 12. *Demographic Information for the Associative Learning Task Participant Sample*

AQ Group	Low ASD Traits (AQ ≤ 17)	High ASD Traits (AQ > 17)	*F*	df	*p*
n	92	99			
Score Total	4-17	18-35			
Sex (Female:Male)*	65:27	63:33	0.35	1, 188	.556
Age (Years)	18.5 (1.7)	18.2 (0.9)	1.92	1, 190	.168
Autism-spectrum Quotient					
Total Score	13.7 (2.7)	21.9 (3.9)	280.75	1, 190	<.001
Social Skills	1.43 (1.3)	3.63 (2.1)	75.17	1,190	<.001
Communication	1.33 (1.2)	3.33 (1.7)	88.09	1,190	<.001
Attention to detail	5.10 (2.0)	5.81 (1.9)	6.27	1,190	.013
Attention Switching	4.36 (1.7)	6.23 (1.6)	63.94	1,190	<.001
Imagination	1.57 (1.1)	2.87 (1.6)	81.02	1,190	<.001
Systematizing Quotient	47.8 (18.1)	50.2 (13.8)	0.86	1, 190	.356
Empathy Quotient	41.8 (7.9)	36.3 (8.4)	19.68	1, 190	<.001

Note. Table reports means (SDs in parentheses) and comparison test statistics. Comparisons tested with ANOVA except where noted. Two participants did not provide their age. I removed four participants who failed to follow the instructions of the task. * Comparison tested with Chi-Squared.

all study procedures and participants documented their informed consent prior to participating.

4.9.2 Procedures

Participants completed the study in a single session. Participants first completed a series of questionnaires (the AQ, as above). Participants then completed two versions of an associative learning task, in which they learned task contingencies based on a non-social (i.e., arrow), or a social stimulus (i.e., face). Participants experienced both types of stimuli within the same task session and I counterbalanced the stimulus order across participants.

4.9.2.1 Associative Learning Task[1]

Participants completed an associative learning task (Sevgi, Diaconescu, Tittgemeyer & Schilbach, 2016; adapted from Behrens, et al., 2008). Each trial of this

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[1] This work was originally intended to examine the task developed by Behrens, et al., 2007, using the gaze stimuli and modeling as implemented in Sevgi, et al., 2016. However, Sevgi, et al.'s original report was unclear with respect to all the task parameters. I therefore relied on both groups' descriptions of the task. My task replicates the design of the task by Behrens, et al., 2007, with one exception. Instead of the original graphical depiction of the "advice" given by the fictitious confederate as in the Behrens task, I used a central gaze cue (a face that looked at one of the cards), as in the Sevgi task, for the "social" condition. However, the reinforcement parameters (i.e., the card values) sampled in the task were drawn randomly from a uniform distribution ranging from 0 to 100 (rather than 1-9 as in Sevgi et al., 2016). My task differed from both previous versions because I included a non-social condition (absent in both the Behrens and Sevgi tasks) in which an arrow, rather than a social stimulus, provided the central cue. Participants completed these conditions in counterbalanced order. Due to a mathematical error that appeared to change the task results, Sevgi, et al., voluntarily retracted their 2016 paper. Since that time, they have significantly revised their modeling, republishing both the data (Sevgi, et al., 2020) and the full set of analysis scripts (available at https://gitlab.ethz.ch/dandreea/mltm). The present analysis implements the Sevgi, et al., 2020, modeling routines within the dataset with one slight change. I scaled the reward parameter down by a factor of 10, to bring it into the range of that reported in Sevgi, et al. (2016; 2020).

task began with a centrally presented fixation cross (1000ms duration). The fixation cross was then replaced with a cueing stimulus in the center of the screen and a pair of colored cards (either blue and red or gold and green) located on the left and right sides of the screen (1000ms duration; Figure 11). Each card contained a number between 0 and 100 (randomly selected from a uniform distribution). Located between the cards was a stimulus (this was either a face [social condition] or an arrow [non-social condition]) that cued them to one of the two cards. In the social task block, the face (which first looked directly at the participant) averted its gaze toward either the left or the right card (750ms) before looking back at the participant. The arrow followed a similar pattern pointing first up and then at one of the cards. Once the face/arrow returned to the center position, participants were able to choose one of the cards by selecting a left or right button press. This display remained visible until the participant selected a card. The computer then framed the selected card for 750ms before providing feedback. If the participant made the correct choice on that trial, the computer displayed a green tick beneath the choice, and the computer added the reward value of the correctly chosen card to a participant’s total score. If the choice was incorrect, the computer displayed a red cross beneath the choice, and the score remained the same. The feedback display was present for 1000ms (see Figure 11).

At the start of the experiment, the experimenter informed participants that the goal of the task was to select the “winning” card from a pair of cards and to try to acquire as many points as possible. Participants were told that if they chose the winning card, they would earn the number of points marked on the face of the card, with their end-of-game monetary bonus determined by their total points. However, the instructions also informed them that sometimes the blue (or gold) card was more likely to be correct and sometimes the red (or green) card was more likely to be correct and that the probability of the blue (gold) or red (green) card being correct on any given trial might change during the experiment. For simplicity, I refer to card color probability going forward as the probability of the blue card being correct. I also note that card color pairings were counterbalanced across stimulus order and participant. Finally, the instructions informed participants that in one block they would see a face in the center of the screen and in another block, they would see an arrow in the center of the screen, both of which would move periodically. The instructions informed them this was to make the experiment more visually appealing for them. They received no additional information about this stimulus (as in Sevgi et al., 2020).

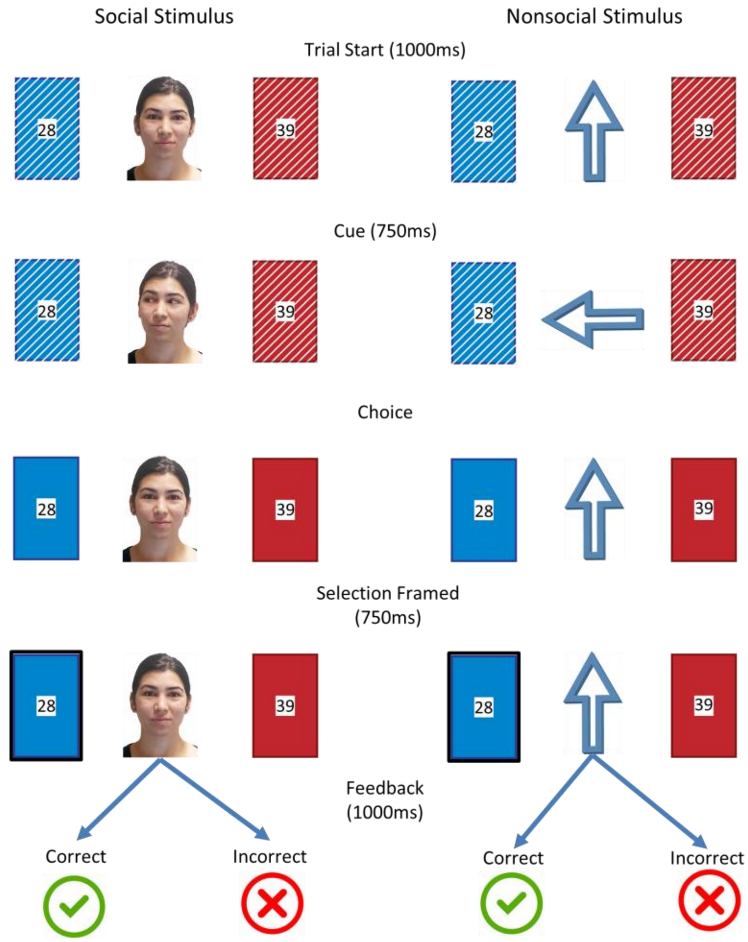

Figure 11. *Associative Learning Task.*

Figure shows examples of social and non-social trials.

During the task, the arrow/face stimulus sometimes indicated the correct selection for the trial, and sometimes indicated the incorrect choice. The arrow/face stimulus shifted between reliable cueing (indicating the correct choice on 75% of trials within a task period) and reliably cueing the incorrect choice location (75% of trials). This contingency shifted (e.g., from mostly correct cues to mostly incorrect cues and vice versa) on trials 30, 40, 50, 60, and 70. I refer to Trials 30-70 as the "volatile" period for cue accuracy.

The probability that the blue card was the correct or winning card also varied across the task. Specifically, for the first 60 trials within a block, the probability of the blue card being correct remained constant. However, on trials, 60, 80 and 100 the probability that the blue card was correct changed (i.e., from being correct on 80% of trials to being incorrect on 80% of trials). I refer to this period (trials 60-120) as the volatile period for the probability that the blue card was correct, as participants must alter their estimates of the likelihood that the blue card is correct (independent of any cue) every 20 trials. Positions of the winning card (left or right) were determined randomly, based on the probability of the blue card being correct in any given period of a task. Overall, participants needed to learn three things in the task: 1) whether the reward was generally associated with the blue card or the red card at any given task trial; 2) the probability that the central cue reliably indicated the card that was rewarded; 3) how these probabilities shifted over time.

Participants completed one block of 120 trials in which the face was the central cue and one block in which the arrow was the central cue in counter balanced order. Additionally, I counterbalanced both the probabilistic schedule for cue accuracy across participants (whether the starting contingency for the central cue was more likely to be accurate or inaccurate) and for the probability of blue being correct (whether blue was more or less likely to be correct). I used E-prime 2.0 to present the stimuli and collect responses (Psychology Software Tools, Pittsburgh, PA).

4.9.3 Questionnaires

As reported above, participants completed the Autism-spectrum Quotient. They were included in the "low" ASD trait group if they scored 17 or less. If they scored 18 or higher, they were classified as "high" in ASD traits.

4.9.4 Data Analysis

To understand the presumably parallel learning systems that guide participants' choice behavior in this task, as well as how participants map different task states to outcomes, I employ an "observing the observer" approach (Daunizeau, Den Ouden, Pessiglione, Kiebel, Stephan & Friston, 2010). This approach is designed to model the integration of environmental stimuli with responses and outcomes to estimate how agents observe the consequences of their actions, given environmental states, and from those consequences, make inferences about the underlying cause-effect relationship(s) active in the environment. Because inferences or predictions based on stimulus-outcome contingencies can be noisy, inaccurate, and can change over time/context, I model uncertainty using a set of one-step update equations, derived from Bayesian principles. This approach relies on a Hierarchical Gaussian Filter (HGF; Mathys, Daunizeau, Friston & Stephan, 2011), which estimates a hierarchical generative model of the environment and its uncertainty (Mathys et al., 2014). The model assigns a probability (likelihood) to each input, by estimating environmental states (e.g., the current probability with which the advice is correct that changes over time) and underlying parameters, given an agent's prior beliefs about how sensory inputs are generated by the external world.

The observing the observer framework assumes two differentiated model components (beliefs about environmental states and responses; Daunizeau et al., 2010; Mathys et al., 2014; Schilbach et al., 2013; Sporns, Chialvo, Kaiser & Hilgetag, 2004) modeled across three integrated levels. Model results are based on the estimation of hierarchically coupled hidden states that describe how agents learn about environmental statistics (in this case, the probability that the blue card is correct, the probability that the gaze advice is valid, and the volatility of both these states). Based on the outcomes of observed decisions (i.e., responses) the model maps an agent's predicted outcome probabilities based on observations of decision outcomes (i.e., accurate/inaccurate gaze, blue or green card correct; level 3). Predicted outcome probabilities or an agent's beliefs about the current state of its environment (level 2), are a function of both observed trial outcomes and the estimated volatility within the current environment (level 1). Together, this model predicts an agent's decisions based on estimates of the agent's beliefs about how the environment gives rise to stimuli, the degree to which those cause-effect relationships are stable, and an agent-specific parameter that estimates the degree to which the agent updates prior beliefs based on decision outcomes. Thus, the model accounts for the deterministic and probabilistic relationships between perceptions of environmental states, the beliefs agents hold about how those states arise and how agents make decisions as a consequence.

From a theoretical standpoint, this model accounts for phasic volatility in the environment (level 1), modeled as:

$$p\left(x_1^{(t)}\right) \sim \mathcal{N}\left(x_1^{(t-1)}, \vartheta\right)$$

the participants' belief about the likelihood of congruent gaze or the blue card being correct (level 2):

$$p\left(x_2^{(t)}\right) \sim \mathcal{N}\left(x_2^{(t-1)}, e^{\kappa x_1^{(t-1)}}\right)$$

as related to predictions about decision outcomes (i.e., whether the gaze advice is actually valid/blue card is actually correct; level 3).

$$p\left(x_3^{(t)} = 1\right) = \frac{1}{1 + e^{-x_2^{(t)}}}$$

According to this model, on any trial (t), $x_1^{(t)}$ follows a Gaussian random walk described by a probability distribution with a mean of $x_1^{(t-1)}$ and a precision of ϑ, a hidden parameter describing environmental volatility. Outcome likelihood on a trial ($x_3^{(t)}$) is modeled as a sigmoid transform of the level-2 model state ($x_2^{(t)}$), which follows the Gaussian distributed estimate of the prior level 2 state ($x_2^{(t-1)}$) whose variance is based on both estimated volatility on the previous trial and a parameter, κ, describing the coupling between model-levels 1 and 2 for the previous time step. A final response prediction layer maps predicted outcomes to responses using a softmax function.

Practically, this work models the dynamics of belief trajectories (i.e., the accuracy and volatility estimates, as well as the precision of these estimates) using four learning parameters. Across stimulus modalities, these parameters represent the coupling between levels of the model for gaze advice (κ_g) and card outcomes (κ_c), as well as the volatility estimates of gaze (ϑ_g) and card outcomes (ϑ_c). The HGF models belief-updating as a precision-weighted prediction error, which can be conceptualized as the surprise an agent experiences upon receiving outcome feedback (e.g., this error is smaller if the observed outcome is either similar to the predicted outcome or if the prediction has low-precision and increases as the outcome differs from prediction and estimated precision of the prediction grows). This belief precision weighting (π) of the prediction error at each trial (t) depends on the low-level volatility estimate (for gaze advice [g] and correct card [c], respectively) and the inferred gaze/card accuracy:

$$\pi_{2,g}^{(t)} = \hat{\pi}_{2,g}^{(t)} + \hat{\mu}_{3,g}^{(k)}\left(1 - \hat{\mu}_{3,g}^{(k)}\right), \pi_{2,c}^{(t)} = \hat{\pi}_{2,c}^{(t)} + \hat{\mu}_{3,c}^{(k)}\left(1 - \hat{\mu}_{3,c}^{(k)}\right)$$

Precision is estimated as:

$$\hat{\pi}_{2,g}^{(t)} = \frac{1}{\frac{1}{\pi_{2g}^{(t-1)}} + exp\left(\kappa_g \mu_{1,g}^{(t-1)}\right)}, \hat{\pi}_{2,c}^{(t)} = \frac{1}{\frac{1}{\pi_{2c}^{(t-1)}} + exp\left(\kappa_c \mu_{1,c}^{(t-1)}\right)}$$

where $\mu_1^{(t-1)}$ represents the participant's prediction about current environmental volatility based on the previous trial.

The model derives subject-specific precision-weighted estimates for outcome likelihood and volatility in parallel, for a given trial t, where $w_g^{(t)}$ and $w_c^{(t)}$ are the current precision estimates of gaze and card cues.

$$w_g^{(t)} = \frac{\zeta\hat{\pi}_{3,g}^{(t)}}{\zeta\hat{\pi}_{3,g}^{(t)} + \hat{\pi}_{3,c}^{(t)}}, w_c^{(t)} = \frac{\hat{\pi}_{3,c}^{(t)}}{\zeta\hat{\pi}_{3,g}^{(t)} + \hat{\pi}_{3,c}^{(t)}}$$

Using these estimates, the model generates a combined belief state, $b^{(t)}$, that integrates posterior expectations for the accuracy inferences associated with both gaze advice and card.

$$b^{(t)} = w_g^{(t)}\hat{\mu}_{3,g}^{(t)} + w_c^{(t)}\tilde{\mu}_{3,c}^{(t)}$$

$\hat{\mu}_{3,g}^{(t)}$ is the logistic sigmoid of the current expectation about gaze accuracy

$$\hat{\mu}_{3,g}^{(t)} = s\left(\mu_{2,g}^{(t-1)}\right) = \frac{1}{1 + exp\left(-\mu_{2,g}^{(t-1)}\right)}$$

and $\tilde{\mu}_{3,c}^{(t)}$ is the transformed belief about current card color (i.e., the probability that the correct card is blue based on the current gaze cue), as inferred from the active gaze cue. For example, during a phase were the gaze advice is generally inaccurate, a gaze toward the blue card would decrease the agent's estimated likelihood that the blue card is correct, and consequently reduce the likelihood of blue card selection.

The parameter ζ represents the additional bias an agent might have toward the social cue (i.e., a participant may have a tendency to follow the social cue) and serves to weight the precision estimates in the model. $\hat{\pi}_{3,g}^{(t)}$ and $\hat{\pi}_{3,c}^{(t)}$ are the inverse variances (precision estimates) for the expected gaze (g) and card (c) accuracies. The model assumes that these estimates follow a Bernoulli distribution and calculates the precision on each trial as:

$$\hat{\pi}_{3,g}^{(t)} = \frac{1}{\hat{u}_{3,g}^{(t)}\left(1-\hat{\mu}_{3,g}^{(t)}\right)}, \hat{\pi}_{3,c}^{(t)} = \frac{1}{\tilde{\mu}_{3,c}^{(t)}\left(1-\tilde{\mu}_{3,c}^{(t)}\right)}$$

Finally, a participant's likelihood of taking the gaze advice was estimated as a softmax transformation of the combined belief state

$$p\left(y^{(t)} = 1 | b^{(t)}\right) = \frac{{b^{(t)}}^{\beta}}{{b^{(t)}}^{\beta} + (1 - b^{(t)})^{\beta}}$$

where β > 0 was an inverse thermodynamic parameter describing a participant's decision randomness. The prior mean and variance for each model parameter, along with the model itself, were exactly as described in Sevgi, et al., (2020). I fit the model on a participant-by-participant and block-by-block (social cue, non-social cue) basis. All model fitting was implemented using purpose written scripts in MATLAB 2020a (The MathWorks, Inc. Natick, MA). The estimates for each model parameter, as well as overall performance metrics, were subsequently analyzed to test the set of proposed hypotheses.

4.10 Results/Discussion

First, I checked to see if participants had performed above chance in all phases of the task to ensure the task properly worked. I found all groups performance differed significantly from chance (see Appendix D for more details). Based on the previous results by Sevgi, et al. (2020), and a wide range of research reports showing difficulties

Table 13. *Exact ANOVA Results for the AQ and Advice Type on Participant Performance, and the Modeling Parameters Fit of the Coupling Parameter, Precision Estimates, and Decision Randomness*

Variable	df	*F*	*p*	η_p^2
Performance (Accuracy)				
AQ	1,181	0.17	.673	.001
Advice Type	1,181	0.69	.405	.004
AQ*Advice Type	1,181	3.91	.049	.021
Coupling Parameter (κ)				
AQ	1,181	0.25	.617	.001
Advice Type	1,181	1.65	.201	.009
AQ*Advice Type	1,181	0.25	.617	.001
Precision Estimates (π)				
AQ	1,181	0.03	.866	<.001
Advice Type	1,181	1.31	.253	.007
AQ*Advice Type	1,181	0.11	.745	.001
Decision Randomness (β)				
AQ	1,181	0.86	.356	.005
Advice Type	1,181	0.51	.475	.003
AQ*Advice Type	1,181	3.58	.060	.019

Note. AQ is the Autism-spectrum Quotient. Advice Type refers to whether participants received social or non-social feedback during the task.

with social versus non-social stimuli (Dawson et al., 1998; Lin et al., 2012; Scott-Van Zeeland et al., 2010), I anticipated that there would be a relationship between ASD traits and task performance such that participants who scored high on the AQ would generally have more difficulty on the task, especially in the social condition. Figure 12,

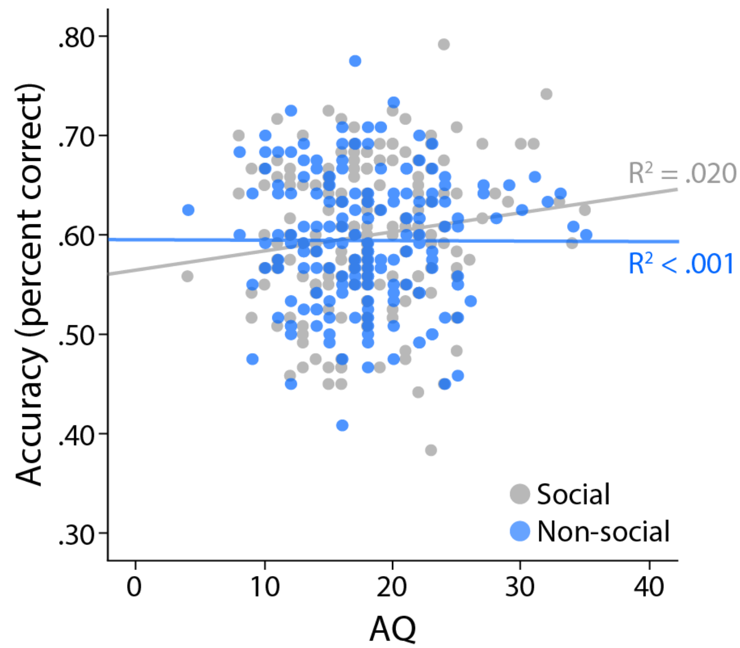

Figure 12. *Relationship between AQ and task performance.*

Social and non-social conditions plotted in orange and blue respectively.

which appears for descriptive purposes, shows the correlation between AQ score and task performance for both social (r (183) = .142, p=.055) and non-social stimuli (r (183) = -.004, p=.960). Results show that neither relationship reaches the threshold for statistical significance. I then employed my standard median split on AQ scores in a mixed-model ANOVA framework with advice condition (social or non-social) to explicitly test for the presence of an interaction between group (high versus low AQ score) and advice type. Results showed no significant main effects for either AQ group, F(1,181) = .179, p = .673, or advice condition, F(1,181) = .697, p = .405. Interestingly, the interaction term did reach the threshold for statistical significance. Contrary to prediction, results showed a group x advice type interaction, $F(1,181)=3.912$, $p = .049$, $\eta^2=.021$, such that the high ASD trait individuals showed slightly better performance in the *social* condition (Figure 13A).

I additionally hypothesized that model parameters associated with how participants treat the advice cue might differ across the groups, depending on whether the advice was social or non-social (the gaze cue or the arrow cue). In particular, I anticipated that the κ parameter, which represents coupling across the levels of the model would show this effect, as would the precision estimates π. I additionally investigated the model parameter β, which is an inverse thermodynamic estimate of decision-randomness. Contrary to prior research and my predictions, I found neither main effects nor interactions for either the coupling parameters or the precision estimates. Interestingly, I did find a marginally significant interaction on the β parameter, $F(1,181) = 3.584$, p =

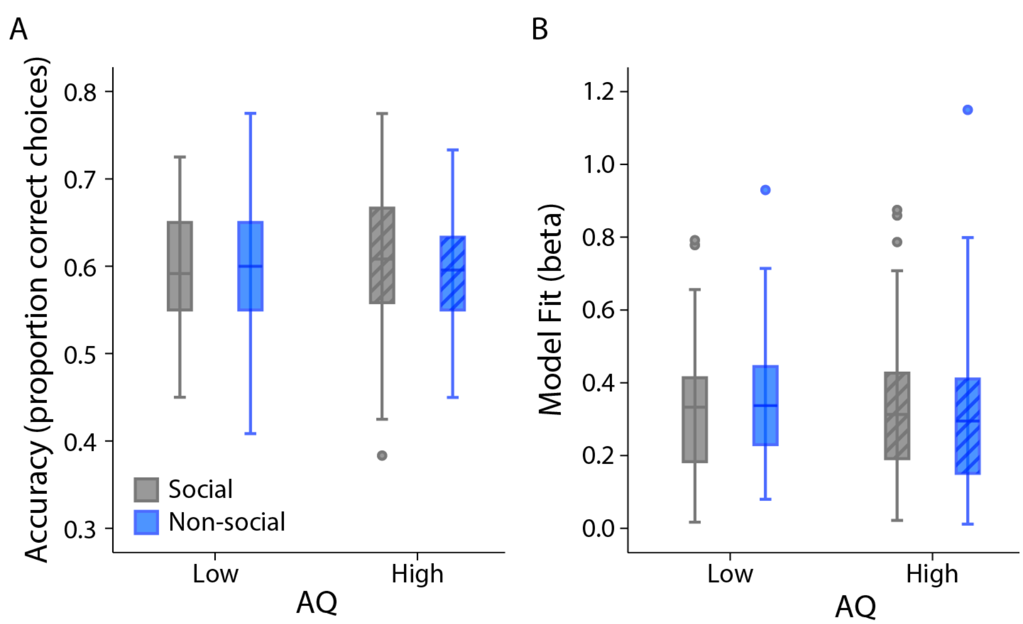

Figure 13. *Associative learning of social and non-social value.*
(A) Accuracy across AQ grouping (B) Model Fit across AQ grouping.

.060, η^2=.019, suggesting that the model estimated somewhat higher decision randomness for participants in the high-ASD trait group (see Figure 13B or Table 13).

4.11 Chapter Discussion

Across all the hypotheses tested in Chapter 4, I found little relationship between task performance and participants' ASD traits on either the probabilistic selection task or the associative learning task. Moreover, performance did not seem to reliably depend on whether the feedback was social or non-social. Where results did show slight group differences and group x task interactions, these differences tended to hover around the thresholds for statistical significance, making it difficult to state with certainty that real and replicable differences existed in the sample. These results, much like in previous chapters, are contrary to previous theoretical assumptions and research findings (Sevgi et al., 2020; Solomon et al., 2011).

However, as in previous chapters, there is an important limitation with respect to the present findings. As with previous chapters, there is an unusual association between AQ and extraversion in one of the three samples. Interestingly, however, the findings from that sample are similar to findings from the other samples in which the association is more typical. Thus, it is possible that this does not affect task results.

Thus, it is worthwhile to consider the possibility that self-reported autism-spectrum traits may not be effective indicators of learning in deterministic and probabilistic environments. I now change focus to investigate how ASD traits and task performances are related to social outcomes and social behavior.

5 ASD Traits and Naturalistic Social Interaction

5.1 Introduction

Deficits in social performance are a hallmark symptom of ASD (American Psychiatric Association, 2013; Baron-Cohen, 1990; Fountain et al., 2012; Landa et al., 2007; Travis & Sigman, 1998). Indeed, many of the earliest ASD indicators that appear in infancy and early childhood are social in nature, including reductions in joint attention, reduced social gaze, and delayed social smiling (Jaswal & Akhtar, 2019; Lockyer & Rutter, 1970; Sigman, Dijamco, Gratier & Rozga, 2004). Interestingly, differences in social behavior may even be present in non-diagnosed individuals who endorse ASD-related traits (Beuker et al., 2013; Goldstein, Naglieri, Rzepa & Williams, 2012; Jobe & White, 2007; Robertson & Simmons, 2013; Rosbrook & Whittingham, 2010). Thus, these individuals may also show alterations in behavior during social interactions. Here, I aim to explore how ASD-related traits manifest in terms of both low-level differences in real social behavior and in social outcomes (i.e., a social partner's perceptions of an interaction). In addition, where possible, I ask how behaviors and social outcomes correlate with task performance to begin the process of relating real social behavior and outcomes with their potential social cognitive underpinnings.

Based on previous theoretical formulations of the social deficits in ASD, one should expect individuals with more ASD-related traits to experience worse social outcomes, and those outcomes should be related to particular types of social behavior. Additionally, one should expect tasks that measure relevant social conditions/motivations to relate to social outcomes. To investigate these ideas, I turn now to data from naturalistic social interactions in which participants "got acquainted" with another participant or, in cases where scheduling did not allow it, an experimenter. These data were collected in the context of the Line Discrimination Task and the original Probabilistic Selection Task (see Chapters 2 and 4) or the Leuven Embedded Figures Task (L-EFT; Chapter 3).

Table 14. *Demographics for Social Interaction Participant Sample*

Variables	
n	333
Sex (Female:Male)	227:103
Age in years	20.80 (6.3)
Autism-spectrum Quotient	
Total Score	19.5 (6.3)
Social Skills	3.2 (2.5)
Attention Shifting	5.3 (2.1)
Attention to Detail	5.9 (2.1)
Communication	2.6 (2.0)
Imagination	2.6 (1.7)
Score Range	6-45
Big Five Inventory	
Extraversion	34.0 (10.2)
Agreeableness	45.3 (8.6)
Conscientiousness	41.6 (7.9)
Neuroticism	32.0 (9.6)
Openness	46.8 (9.1)
Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS)	
BIS	22.7 (3.8)
Fun Seeking	12.7 (2.7)
Drive	11.8 (2.5)
Reward Responsiveness	17.9 (2.4)

Note. Age and questionnaire measures show means (standard deviations in parentheses). Three participants did not report sex, four participants did not report age and seven participants did not complete the BFI.

5.2 Methods

5.2.1 Participants

Recruited in the context of previous samples within this dissertation (see Chapter 2.2.1. and Chapter 3.1.1 for participant details), 333 participants completed a naturalistic "getting acquainted" social interaction alongside either the line discrimination and probabilistic selection tasks (n = 127) or the Leuven embedded figures task (n = 206). For demographic information on this sample refer to Table 14.

5.2.2 Procedure

Participants completed a "getting acquainted" type naturalistic social interaction in the context of a longer laboratory session. Interactions were 5-minutes long, unscripted and completed with either an experimenter (if another participant was unavailable; N=69), or another participant (N=264). When participants interacted with an experimenter, the experimenter behaved as naturally as possible. Immediately after the social interaction, both interaction partners (including the experimenter when applicable) completed a 16-item questionnaire in which they reported how much they liked their social partner (e.g., "I would like to get to know my conversation partner better"; , α = .97) and about the quality of their interaction (e.g., "The interaction felt natural"; , α = .98; see Gilder & Heerey 2019). These questions are based on a modified Desire for Future Interaction scale (Coyne, 1976). This measure shows excellent cross-participant correlations suggesting that these ratings are reliable and valid measures of perceptions of a social partner and interaction (e.g., Gilder & Heerey 2019; Heerey & Crossley, 2014).

Participants rated each item on a visual analogue scale anchored with ‘strongly agree’ to ‘strongly disagree’.

Participants completing this task in the context of the Leuven Embedded Figures Task (N=206; Chapter 3) were video-recorded for offline analysis and the interaction data electronically coded (technical difficulties caused a save failure for 4 participants’ video data so these participants were excluded from video analyses). Noldus FaceReader 8.0 software (Noldus, 2019) automatically coded participants facial behavior. FaceReader models expressive behavior on a frame-by-frame basis and classifies that behavior in terms of Facial Action Coding System (FACS; Ekman & Friesen, 1976; Ekman, Friesen & Hager, 2002) “action units” (AUs). Each action unit represents the contraction of a single muscle group and simultaneously displayed action units contribute to facial expressions (e.g., the contraction of the zygomaticus major and orbicularis oculi muscles that characterize the genuine smile; Ekman & Friesen, 1976; Ekman et al., 2002).

To detect AUs, FaceReader processes information from video input in three key steps. First, it relies the Viola-Jones face detection algorithm to “find” the face within the frame (Viola & Jones, 2001). Second, it creates a 3D model using the Active Appearance Method (AAM) described by Cootes and Taylor (2000). Briefly, the AAM is trained on a database of images that describes 500+ points in the face. Key facial aspects include 1) points that enclose the face and 2) facial points that enclose easily recognizable features like lips, eyes and nose. Third, facial expression classification relies on an artificial deep-learning neural network (Bishop, 1995), trained on a database with over 10,000 images; a method known as ‘Deep Face’ classification system (Giarelli et al., 2010). Additional detail on the functioning of this classification system is available in the FaceReader Methodology Note (Loijens & Krips, 2019).

FaceReader has been shown to have good convergent validity with its ability to recognize and correctly classify between 80-88% of emotions within the Warsaw Set of Emotional Facial Expression Pictures (WSEFEP) and Amsterdam Dynamic Facial Expression Set (ADFES), which is comparable to human classification (85%; Lewinski, den Uyl & Butler, 2014; Skiendziel, Rösch & Schultheiss, 2019). Additionally, FaceReader shows similar levels of reliability to the interrater reliability of expert human coders (.69 versus .7; Lewinski et al., 2014). Once FaceReader coded the data, I calculated composite scores to examine the proportion of frames that were active (activity greater than 10% of baseline) for each Action Unit as a metric of "expressivity".

5.2.3 Data Analysis

This study has three main goals: 1) to examine how ASD-related traits predict social outcomes; 2) to correlate task performance with social outcomes; and 3) to explore ASD-related differences in social behavior. For the first question, I analyzed all participants who had completed both the AQ and partner-rated interaction scale (n = 333). Due to the large sample size for whom both AQ data and partner-rated interaction quality and liking measures were available, I examined the data using linear regression, rather than the high versus low symptom groupings from previous chapters. I implemented two regression models, with partner-rated interaction quality and partner-reported liking of participants as the criterion variables. I then entered the individual subscales of the AQ to examine how the different types of ASD-related traits predict social outcomes. I also ran a parallel version of these analyses using the subscales of the Multidimensional Social Competence Scale (MSCS) to examine the consistency of these results in a different self-reported ASD-related traits scale. However, as the MSCS was only presented to one participant sample (those who completed the L-EFT), this exploratory analysis includes only 206 participants.

To answer the second question, about the link between social outcomes and task performance, I used a correlational analysis to examine the relationship between social outcomes (i.e., partner-reported likeability and interaction quality) and task performance in the Line Discrimination Task (discriminability and criterion), the Probabilistic Selection Task (trials to criterion, win-stay, and lose-shift behavior) and the Leuven Embedded Figures Task (response time and error rate). These tasks were completed by different participant samples. Therefore, 127 participants were involved in the correlational analysis between social outcomes and task performance in the Line Discrimination Task and the Probabilistic Selection Task, and 206 participants were involved in the correlational analysis between social outcomes and task performance in the Leuven Embedded Figures Task.

Lastly, based on anecdotal observations of social behavior amongst high and low-AQ scoring pilot participants, one of the striking observations our laboratory group has noticed is that people who report greater levels of ASD-related traits appear to be less expressive during their interactions (Kleberg, Högström, Nord, Bölte, Serlachius & Falck-Ytter, 2017; Stagg, Slavny, Hand, Cardoso & Smith, 2014). Using this idea as an exploratory hypothesis, I examined participants' expressivity by calculating the proportion of time (in frames) that various action units are active during the interaction.

To examine ASD-related differences in social behavior, I then correlated AQ scores with these activity scores, as well as examining the relationship between these activity scores with partner-reported liking, interaction-quality and L-EFT performance.

5.3 Results

5.3.1 Social Interaction Outcomes

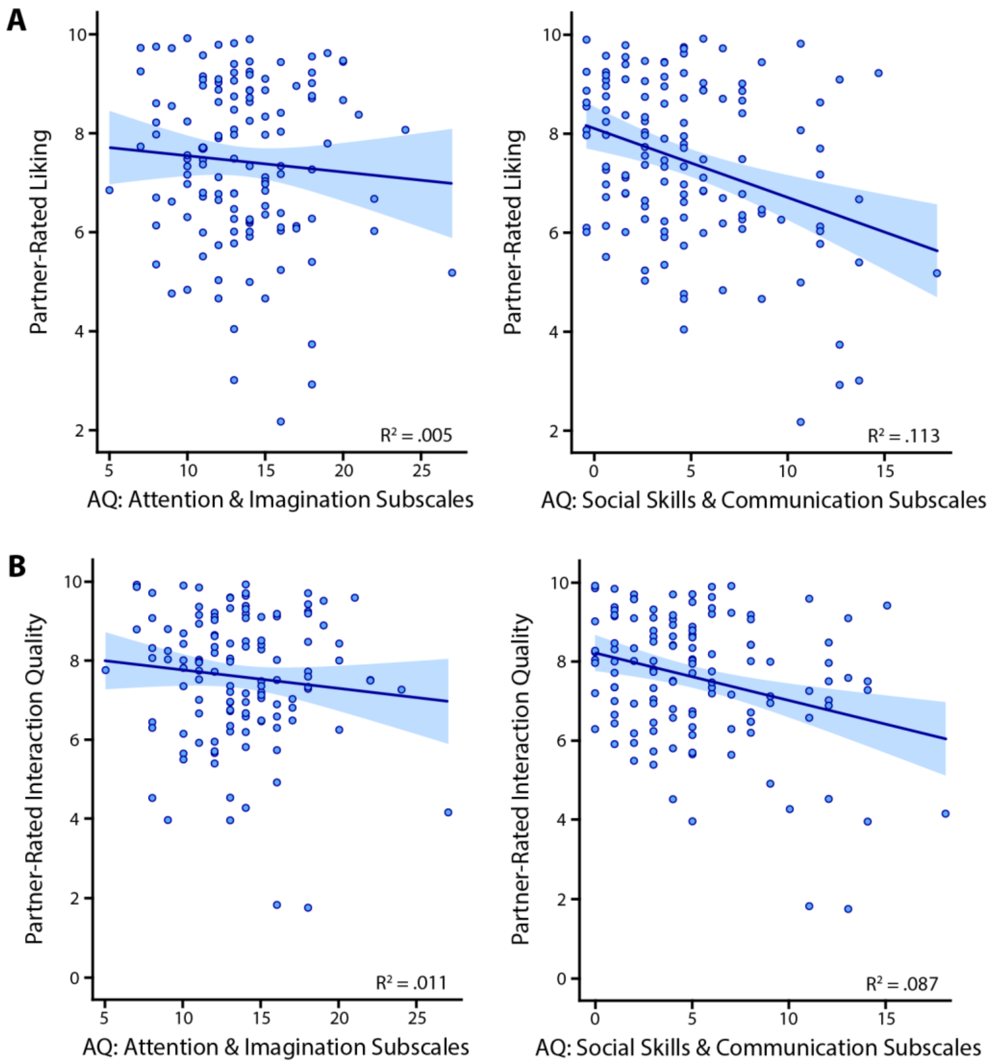

Figure 14. *Associations between AQ Social Skills and Communication subscales with social outcomes compared to other AQ subscales.*

(A) Participant combined AQ subscale scores correlation with Partner Rated Liking (B) Participant combined AQ subscale scores correlation with Partner Rated Interaction Quality

Results from the linear regressions predicting partner-rated liking and interaction quality from the AQ subscales showed that together the AQ subscales explained a significant amount of the variance in how much a social partner liked a participant ($F(5, 332) = 6.745$, $p < .001$, $R^2 = .094$) and the partner's perception of interaction quality ($F(5, 332) = 6.480$, $p < .001$, $R^2 = .090$). The AQ's social skills and communication subscales, both of which generally assess social communication competency, significantly predicted partner-rated liking and interaction (see Table 15, Figure 14; Table 16 shows the same set

Table 15. *Regression Analysis for Social Interaction Ratings and AQ subscales*

Model	*B*	*95% CI*	β	*t*	*p*
Partner Rated Liking					
$AQ_{Social\ Skills}$	-1.409	-2.379; -.439	-.195	-2.857	.005
$AQ_{Attention\ Shifting}$	-0.096	-1.189; .996	-.011	-0.174	.862
$AQ_{Attention\ to\ Detail}$	-0.074	-.988; .841	-.008	-0.159	.874
$AQ_{Communication}$	-1.500	-2.737; -.264	-.161	-2.387	.018
$AQ_{Imagination}$	0.881	-.291; 2.053	.082	1.478	.140
Partner Rated Interaction Quality					
$AQ_{Social\ Skills}$	-1.354	-2.182; -.526	-.220	-3.219	.001
$AQ_{Attention\ Shifting}$	0.136	-.796; 1.068	.018	0.288	.774
$AQ_{Attention\ to\ Detail}$	-0.481	-1.261; .226	-.065	-1.213	.226
$AQ_{Communication}$	-1.150	-2.205; -.095	-.145	-2.145	.033
$AQ_{Imagination}$	0.633	-.367; 1.633	.069	1.246	.214

Note. AQ = Autism-spectrum Quotient.

of analyses using the MSCS subscales). However, none of the other AQ subscales predicted differences in either social outcome variable.

Using a linear regression with the MSCS sub-scales entered, I found that together the MSCS subscales explained a significant amount of the variance in how much a social

Table 16. *Regression Analysis for Social Interaction Ratings and MSCS subscales*

Model	*B*	*95% CI*	β	*t*	*p*
Partner Rated Liking					
MSCS *Social Monitoring*	0.488	-0.01; 0.99	.187	1.938	.054
MSCS *Social Inferencing*	-0.264	-0.85; 0.32	-.080	-0.885	.377
MSCS *Demonstrating empathic concern*	0.711	0.15; 1.27	.234	2.503	.013
MSCS *Social knowledge*	0.161	-0.57; 0.89	.040	0.436	.663
MSCS *Verbal conversation skills*	0.163	-0.38; 0.71	.050	0.589	.556
MSCS *Nonverbal conversation skills*	0.070	-0.50; 0.64	.024	0.241	.810
MSCS *Emotion regulation*	-0.215	-0.68; 0.25	-.073	-0.907	.366
Partner Rated Interaction Quality					
MSCS *Social Monitoring*	0.149	-0.25; 0.55	.074	0.738	.461
MSCS *Social inferencing*	.036	-0.44; 0.51	.014	0.152	.879
MSCS *Demonstrating empathic concern*	-0.082	-0.53; 0.37	-.035	-0.362	.718
MSCS *Social knowledge*	-0.102	-0.69; 0.48	-.033	-0.343	.732
MSCS *Verbal conversation skills*	-0.165	-0.60; 0.27	-.065	-0.742	.459
MSCS *Nonverbal sending skills*	0.563	0.11; 1.02	.247	2.428	.016
MSCS *Emotion regulation*	0.148	-0.23; - 0.52	.065	0.778	.438

Note. MSCS = Multidimensional Social Competency Scale partner liked a participant (F(7, 205) = 4.847, $p < .001$, $R^2 = .084$) and the partner's

Table 17. *Correlation Analysis for Social Interaction Ratings, Line Discrimination Task Probabilistic Selection Task, L-EFT, Letter Number Sequencing Task and the RMIET*

Task	Partner Rated Liking	Partner Rated Interaction Quality
Line Discrimination Task		
Social		
Criterion Difference	-.052 (.633)	.002 (.987)
Non-Social		
Criterion Difference	.017 (.875)	.133 (.218)
Probabilistic Selection Task		
Social		
Trials to Criterion		
100/0 Pairing	-.031 (.768)	-.016 (.878)
60/40 Pairing	-.100 (.338)	.051 (.625)
Win-stay Behavior	**.215 (.035)**	.083 (.419)
Lose-shift Behavior	-.120 (.244)	-.036 (.729)
Non-Social		
Trials to Criterion		
100/0 Pairing	.031 (.762)	-.029 (.777)
60/40 Pairing	.052 (.611)	.060 (.560)
Win-stay Behavior	.027 (.792)	.052 (.606)
Lose-shift Behavior	-.042 (.679)	-.059 (.560)
L-EFT		
Response Time (RT)		
Total	-.114 (.103)	-.022 (.753)
Error Rate		
Total Error Rate	.023 (.741)	-.001 (.986)
Letter Number Sequencing		
Total Score	.015 (.829)	.025 (.721)
RMIET		
Total Score	.017 (.806)	.052 (.453)

Note. L-EFT = Leuven Embedded Figures Task. RMIET = Reading the Mind In the Eyes Task. p-values are in parentheses. Bold correlations indicate significant correlations using an uncorrected decision criterion. Notably, after accounting for multiple correlations, none of these analyses reached statistical significance. The correlational analyses that include the Line Discrimination Task and the Probabilistic Selection task used an N of 127, while the correlational analyses that included the L-EFT, Letter Number Sequencing Task and the RMIET used an N of 206.

perception of interaction quality ($F(7, 205) = 4.177$, $p < .001$, $R^2 = .076$). The MSCS Demonstrating Empathetic Concern subscale was a significant predictor of partner rated liking ($p = .013$) and the Social Monitoring subscale was a marginally significant ($p = .054$). The MSCS Nonverbal Conversation Skills subscale was the only subscale to be a significant predictor of partner rated social interaction quality. None of the other MSCS subscales predicted differences in social outcomes (see Table 16).

To assess whether partner-rated interaction ability linked to task measures, I examined the correlations between partner-rated liking and interaction quality and task performance in the line discrimination task (response bias) the probabilistic learning task (trials to criterion, win-stay behavior, and lose-shift behavior), the L-EFT (Response Times and Error Rate), the Letter Number Sequencing task from the Wechsler Adult Intelligence Inventory (Wechsler, 1997) and the RMIET (see Table 17).

5.3.2 Social Interaction Behavior

To examine the video data, I reduced the many possible comparisons by excluding action units that were active less than 10% of the time in the full sample. In a sample this small, examining statistics such as proportion of activation time for low-frequency behaviors can generate spurious findings. I began by examining the relationships between two important action units and the social outcome variables (partner-rated liking and interaction quality). These action units included AU12 (associated with zygomaticus major activity or smiling) and AU43 (eye closure; which is active both when the eyes are fully closed, as with a blink, or when they are fully downcast, as when the eyes are cast directly down toward the floor). I selected these action units because evidence suggests that both smiling and gaze behavior are important in face-to-face social interaction (Ho, Foulsham & Kingstone, 2015; Johnston, Miles & Macrae, 2010; Kampe, Frith, Dolan & Frith, 2001; Shore & Heerey, 2011; Vernetti et al., 2018). Neither of these action units was significantly associated with liking. Interestingly, AU43 was significantly negatively associated with Interaction Quality (r (198) = -.169; p=.017), such that the more time participants spent with a downcast gaze the worse their

Table 18. *Correlations between AQ subscale scores, MSCS subscale scores, L-EFT performance, and Action Unit activation*

Variable	AU12: Lip Corner Puller	AU43: Eyes Closed
Autism-spectrum Quotient (AQ)		
Social Skills	**-.147 (.041)**	**.168 (.020)**
Communication	-.088 (.220)	-.036 (.618)
Multidimensional Social Competency Scale (MSCS)		
Social Monitoring	.072 (.318)	-.018 (.797)
Social Inferencing	.052 (.470)	-.032 (.655)
Demonstrating Empathetic Concern	.091 (.204)	-.085 (.237)
Social Knowledge	.115 (.109)	.003 (.968)
Verbal Communication Skills	.104 (.146)	-.001 (.986)
Non-Verbal Communication Skills	.075 (.298)	-.132 (.065)
Emotion Regulation	.109 (.129)	-.038 (.592)
Leuven Embedded Figures Task (L-EFT)		
Response Time	-.008 (.912)	-.024 (.743)
Error Rate	**.142 (.049)**	**-.187 (.009)**

Note. Table shows Pearson correlations (p-values are in parentheses). Bold typeface indicates statistically significant correlations.

social partners rating the interaction quality. This suggests that altered gaze behavior is associated with partner interaction quality ratings.

Next, I examine how these behaviors relate to autism-spectrum quotient scores. Because the Social Skill and Communication subscales of the autism-spectrum quotient were the only subscales that were significantly associated with social outcomes, I excluded the other autism-spectrum quotient subscales and focused only on these to reduce the number of statistical tests. Notably, the data showed that AU12 (associated with zygomaticus major activity or smiling) was significantly less active for participants reporting with higher levels of ASD Social Skill-relevant traits. Additionally, the Social Skills subscale was positively associated with AU43 (eye closure), suggesting that participants endorsing more ASD social traits spend greater amounts of time with the eyes either closed or significantly downcast. Table 18 shows exact statistics. Additionally, I explored possible associations between the MSCS and facial activity. I found no MSCS subscales associated with action units of interest (AU 12 and 43; see Table 18).

Finally, I explored the data for the presence of any relationships between action units and performance on the L-EFT. There was no significant relationship between these action units and response times on the L-EFT. Interestingly, I did find associations between error rates on the L-EFT and action units. AU12 (smiling) showed a positive relationship with error rate such that participants who made more errors on the task, also smiled more during the social interaction. AU43 (eye closure) showed the inverse relationship, such that participants who made more L-EFT errors engaged in less eye closure or downcast gaze with their partners (see Table 18).

5.4 Chapter 5 Discussion

In the face-to-face social interaction, participants who reported higher levels of ASD-related traits, specifically those associated with social communicative skill, experienced worse social outcomes, as operationalized by partner ratings of interaction quality and liking. This suggests that there are subtle differences in social behavior across the spectrum of ASD-related traits. This idea is supported by findings from the social behavior analysis, that show that those reporting more in ASD-related traits appeared to smile less and were more likely to show abnormal patterns of eye-gaze behavior – more specifically, closing or casting the eyes downward to the floor positively correlated with self-reported ASD-related traits. Taken together, these data suggest that the subtle behavioral differences in face-to-face behavior associated with the higher end of the ASD-trait spectrum may lead to poorer perceptions of social interaction between participants and their interaction partners.

Unfortunately, the social behavior and social outcome results showed little relationship with task performance. Interestingly however, there was evidence of a relationship between the action unit associated with gaze lowering and performance on the L-EFT. Altered gaze behavior may well be associated with global versus local processing biases, however, due to the exploratory nature of this analysis, it will be important to replicate this result. Nonetheless, these results suggest that researchers should be cautious about linking laboratory task performance to social behavior in the absence of data that lends these direct comparisons empirical support.

Although interesting, there are limitations to the present findings. Specifically, these interactions took place only between strangers in the laboratory context. Although they were unmanipulated and unscripted, it is therefore possible that participants' behaviour was not the same as it is typically in non-laboratory contexts. Additionally, because participants had the opportunity to talk to only one other partner, the simple random assignment of participants to partners might have affected results. Future studies might attempt "round robin" interaction designs in which participants speak with several partners. In such designs, it is possible to distinguish "actor", "partner" and dyad-level effects (Kenny, 1996; Kenny, Kashy & Cook, 2006). This would certainly provide a more wholistic picture of how ASD-related traits might impinge on naturalistic conversation.

6 General Discussion

Contrary to expectations, the data in this dissertation fail to confirm almost all the previous predictions with respect to how they should relate to self-reported autism-spectrum traits. Thus, although there was clear evidence that the tasks functioned as intended (e.g., participants took longer to learn more probabilistically reinforced contingencies), none of the main tasks showed the anticipated differences between those scoring high and low on the AQ. That is, the present data failed to replicate previous results in the literature. Indeed, the only clear and consistent evidence for ASD-group-related differences in this entire dissertation comes from the naturalistic social interaction task. I address each individual research question in turn.

6.1 Current Findings and the Social Motivation Hypothesis

In Chapter 2, I investigated the link between ASD-traits and social and nonsocial reward sensitivity and the link between ASD-traits and the value attributed to social and non-social rewards. I examined participants' general sensitivity to reinforcement using an asymmetric reinforcement task (Pizzagalli, Jahn, & O'Shea, 2005) that allowed the quantification of reward sensitivity based on the development of response bias in the presence of social versus non-social rewards. To examine how the subjective value of a smile relates to ASD-traits, I conducted a secondary analysis of a smile valuation task developed by our lab (e.g., Heerey & Gilder, 2019). Overall, I found no relationship between task performance and participants' ASD traits on either the line discrimination task or the smile valuation task for non-social rewards or, surprisingly, for social rewards.

The results from this chapter are therefore contrary to much of the literature examining the social motivation hypothesis (Chevallier et al., 2012; Clements et al., 2018; Demurie et al., 2011, Galli et al., 2019; Klin et al., 2002; Miligan et al., 2007; Mundy, 2009; Rozga et al., 2011; Scheeren et al., 2013). While some of the findings were consistent with previous literature, such that I found individuals are more sensitive to non-social asymmetric reinforcement, compared to social asymmetric reinforcement (Kohls, Peltzer, Herpertz-Dahlmann & Konrad, 2009; Bottini, 2018), the majority of the findings were inconsistent with many of the theoretical predictions of the social motivation hypothesis. For example, I found no link between ASD-traits and the rate at which one sensitizes to monetary rewards or social rewards. Additionally, I found no evidence for the prediction that individuals who report many ASD traits should have ‘deficits representing social rewards’ and should therefore value social rewards less (Chevallier et al., 2012). Taken together, none of the findings in this chapter support a potential social motivational mechanism as a feasible explanation for the behavioral differences seen across the autism-spectrum, especially, in the general population.

While this is some limited literature that shows no difference in how children with ASD value smiles (Ewing, L., Pellicano & Rhodes, 2013), the current investigation is one of the first to do so using a large double-blinded general population sample. The current failure to confirm predictions is deeply concerning for the validity of the social motivation hypothesis, because if ASD traits have no impact on the value individuals ascribe to social and non-social rewards, then the hypothesis holds little impact or importance to ASD literature.

One possibility for the present failure to confirm prior results may relate to the general-population sampling methodology. Interestingly, however, a meta-analysis by Bottini (2018), found that only 57% of the literature that uses clinically diagnosed populations find the outcomes predicted by the social motivation hypothesis. While Bottini suggests that this may be because the current hypothesis is too restrictive, the failure of this result in the present, reasonably well-powered samples suggest that perhaps the speculation that ASD is associated with reduced social reward valuation is not correct.

Lastly, and what should be most concerning to proponents of the social motivation hypothesis, are the findings from Chapter 5, where I was unable to find any association between reward sensitivity and social outcomes. As the social motivation hypothesis was created to explain how deficits in social motivation result in the social deficits seen in ASD (Abrams et al., 2013; Chevallier et al., 2012, Kohls et al., 2012; Mundy, 2019), then it should be deeply concerning when tasks used to measure concepts like reward sensitivity have no relation to real life outcomes. The absence of an association between task performance and real-life social outcomes suggests that many of the predictions and assumptions of the social motivation hypothesis, might be limited to laboratory settings and not transfer to naturalistic settings.

While it was not my goal, the absence of any sort of support for the social motivation hypothesis in this dissertation, combined with concerns about this theory in the existing literature (e.g.,‘social deficits’ having non-social explanations, findings better explained with different frameworks etc.; Jaswal & Akhtar, 2019; Kapp, et al., 2019; Uljarević et al., 2019), raises questions about the validity and importance of this hypothesis. Considering all of this, the social motivation hypothesis, does not appear to be a fruitful or productive theory to explain the symptoms of ASD.

6.2 Current Findings and the Weak Central Coherence Hypothesis of Autism

The weak central coherence hypothesis is predicated on the idea that individuals with ASD have local processing biases at the cost of global processing (Frith 1989; Plaisted, 2015). In Chapter 3, I investigated the link between ASD-traits and participants' preference for global versus local processing using the Leuven Embedded Figures Task, which has been shown to relate to ASD-related traits (de-Wit, et al., 2017). As with previous literature I found that task performance declined as the task became harder (e.g., the target image became more complex, asymmetrical, or blended into the background image more; de Wit et al., 2017, Van der Hallen et al., 2018). However, unlike previous literature I was unable to find strong support for the idea of weak central coherence.

The current findings are therefore consistent with a growing pool of literature that is unable to find local processing biases in individuals with ASD, or with high levels of ASD traits (Hayward et al., 2018; Hoy et al., 2004; Mottron et al., 2003; Muth et al., 2014). The current findings are therefore inconsistent with the predictions of the weak central coherence hypothesis. One reason for this might be that the tasks being used to test for processing biases are inefficient and inconsistent (Lawson, 2011; Milne & Szczerbinski, 2009; Van der Hallen, Evers, Brewaeys, Van den Noortgate & Wagemans,2015), or that the weak central coherence hypothesis of ASD, is a much more limited and narrow in scope than previously proposed. Overall, none of the findings in

Chapter 3 support the idea that processing biases are likely to underpin ASD-traits across the autism spectrum.

Interestingly, although I was unable to find any sort of association between performance on the L-EFT and social outcomes (i.e., partner-rated liking and interaction quality), I did find a small but significant correlation between errors on the L-EFT and social behavior, such that those who made more errors were also those individuals who smiled more and engaged in more typical eye gaze behavior. However, the fact that L-EFT performance was not related to ASD traits makes this particular finding difficult to interpret. Overall, it appears that while there is some support for local/global processing relating to social interaction data, it is very limited in scope and is therefore unlikely to be a strong explanation for ASD traits (Muth et al., 2014).

6.3 Current Findings and the Probabilistic Learning Hypotheses of Autism

In Chapter 4, I investigated the link between ASD-traits and an individuals' ability to learn from social and non-social rewards that are either deterministically or probabilistically reinforced as well as the link between ASD-traits and the degree to which people could learn to integrate information from multiple cues with changing contingencies. To test the link between ASD traits and probabilistic learning from rewards I used a probabilistic selection task (Frank, Seeberger & O'Reilly, 2004; Solomon et al., 2011). To investigate the link between ASD-traits and participants' ability to integrate information from a changing environment I used an associative learning task (Sevgi, Diaconescu, Tittgemeyer & Schilbach, 2016; Behrens, et al., 2008).

Overall, I found no strong relationships between task performance and participants' ASD-traits on either the probabilistic selection task or the associative learning task.

One of the key predictions made by some models of probabilistic learning is that individuals with ASD, or those high in ASD traits, learn more slowly from probabilistic environments/feedback compared to deterministic environments/feedback. In my first investigation, I examined whether ASD traits impacted the rate which participants learned from probabilistic and deterministic feedback using both social and non-social feedback in a probabilistic selection task that has been previously used (D'Cruz et al., 2013; Solomon et al., 2015; Solomon et al., 2011). Contrary to previous results, I found no support for the idea that ASD traits affected the rate at which individuals learn from probabilistic feedback, regardless of whether the feedback was social or non-social. The only behavioral difference I found in the probabilistic selection task was individuals with more ASD-traits engaged in less win-stay behavior compared to individuals with fewer ASD traits, which is consistent with previous literature in this field (Solomon et al., 2011).

In addition to looking at how individuals learned from probabilistic feedback, I was also interested in the degree to which participants learned from environmental cues using an associative learning task. Previous results suggest that individuals with ASD traits learn more slowly in periods of environmental volatility (i.e., when reinforcement contingencies fluctuate in the degree to which they are reliable; Sevgi et al., 2020). Unfortunately, I was unable to replicate those findings in the current dissertation. It should be noted that compared to the previous findings, using a sample of 18 high and 18 low AQ participants, the current sample had far greater statistical power (over five times the sample size) and was double-blind in design. These findings therefore suggest that 1) these tasks are not sensitive enough to measure the hypothesis within a general population sample; 2) for the general population, conclusions about people's abilities to learn from probabilistic environments/feedback, cannot be tied to ASD traits; 3) that the previous smaller sample sizes and non-double-blind methods affected prior results; or 4) that learning mechanisms are not sufficient explanations for ASD-related traits.

6.4 ASD Traits and Social Interactions

Finally, Chapter 5, investigated the link between ASD-traits and social behavior in a naturalistic interaction and subsequent interaction outcomes as well as the link between social interaction outcomes and several tasks (i.e., line discrimination task, probabilistic selection task and the L-EFT). I additionally explored potential links between social behavior and ASD-traits as well as L-EFT performance.

As predicted, there were clear associations between the ASD traits as measured by both the AQ and the MSCS and social outcomes. It is also important to note that these relationships only existed for the social skills and communication subscale for the AQ and the empathetic concern and nonverbal conversation skills subscales of the MCSC. Thus, these measures of ASD-related traits do appear to show some validity with respect to naturalistic social behavior – even though they failed to predict task outcomes.

These data showed that ASD-traits associated with social skill and communication abilities appear to predict partner liking and interaction quality, such that the more ASD-traits an individual endorsed, the less likable their partner thought they were and the more effortful the partner thought the interaction was. Results also showed that ASD-traits related to behavioral differences across individuals such that individuals who reported more ASD-traits were less expressive during their interactions. Specifically, they smiled less and spent more time with their eyes cast downwards compared to those who endorsed fewer ASD-traits.

Interestingly, the only task that related to naturalistic social behavior was the L-EFT. Specifically, errors on the L-EFT were associated with smiles and eye gaze behavior during the interaction, even though the L-EFT itself did not correlate with interaction outcomes. Overall, there was a clear relationship between ASD-traits and social interaction behavior and outcomes, but no conclusive association between social behavior and cognitive and motivation-based tasks in the general population samples I recruited. Thus, it appears that the AQ and its social subscales (social skills and communication) are reasonable measures of both social outcomes and important social behaviors like smiling and eye gaze.

6.5 Implications and Limitations

This dissertation contains several critical implications for research into autism spectrum diagnoses. First, it appears that ASD traits, as measured by the AQ, are clearly related to social outcomes and naturalistic social behavior in the general population. This finding is even more significant considering first, that the participants within the samples examined here did not have autism spectrum diagnoses. That is, even the high-AQ individuals were socially high functioning enough to be classified as members of the general population. Of course, that does not rule out the possible presence of ASD diagnoses within the sample, however, given the AQ score distributions, diagnosed individuals were unlikely to comprise a large number of participants. Second, the social interaction task, in which people engage in the basic social “chit-chat” that people use as they get to know one another, was entirely naturalistic and not designed to measure contrived sets of “social skills” in acted scenarios (e.g., Haring & Lovinger, 1989; Mcintosh, Vaughn & Zaragoza, 1991; Schumaker & Ellis, 1982; Simpson, Langone & Ayres, 2004; Truzzi, Setoh, Shinohara & Esposito, 2016; von dem Hagen & Bright, 2017). Nonetheless, evidence show clear associations between ASD traits and important social behaviors (i.e., smiling and eye gaze behavior). These findings suggest that even non-clinical differences in ASD traits can result in differences in social outcomes (partner-perceived interaction quality and liking) and social behaviors. Thus, results lend support to the idea that autism traits may indeed occur on a spectrum and that those traits, even where mild, may have implications for the quality of social support, work relationships, and other domains in which social ability plays a significant role. Further understanding of these symptom/outcome relationships will certainly be important moving forward.

In contrast with the strong associations between ASD traits and natural social behavior and outcomes, the absence of clear associations between ASD traits and task outcomes is both surprising and concerning. Several potential explanations arise from these findings. First, it might be the case that despite wide speculation that such skills underpin basic social behavior (e.g., Jaswal & Akhtar, 2019; Kapp et al., 2019; Muth et al., 2014), that these tasks have little real association with social behavior. It is possible that these tasks do not measure the constructs they claim to measure with adequate sensitivity and/or precision. That is, it remains possible that there are *theoretical* links, but that these tasks do not underpin natural social behavior. Similarly, it is certainly possible that these tasks are not sensitive enough to capture performance differences between high and low AQ groups used in the present dissertation. For example, the individuals in the high AQ groups may have the ability to achieve equal performance on such tasks as their low-AQ peers, despite their endorsement of ASD-related traits.

Second, I have only used a small number of tasks to answer each of the questions I have asked in this dissertation. While each of the tasks I have used in this dissertation has generated support for the idea of ASD-related differences, there are a variety of other tasks in each theoretical domain that might have showed these associations (Bottini, 2018; Carr & Walton, 2014; Chatzisarantis et al., 2006; Conson et al., 2013; Dawson et al., 1998; Deruelle et al., 2006; Elsabbagh et al., 2013; Gliga et al., 2009; Grinter et al., 2009; Jolliffe & Baron-Cohen, 1999; Lin et al., 2012; Manning et al., 2017; Muth et al., 2014; Pellicano et al., 2006; Snowling & Frith, 1989). Nonetheless, it is unclear whether these other existing tasks are more sensitive to high- low-ASD-trait group differences, and if so, which ones.

A second possibility is that there are fundamental problems with task methods in the general literature. Specifically, these may relate to small sample sizes which are almost universal in this literature (e.g., Bottini, 2018; Dawson et al., 1998; Lin et al., 2012; Manning et al., 2017; Muth et al., 2014; Sevgi et al., 2020; Solomon et al., 2015; Solomon et al., 2011, Van der Hallen et al., 2018). Evidence shows that when sample sizes are smaller, results may be more prone to Type I error (Lin, 2018; Rom & McTague, 2020; Simonsohn, 2015), poor generalization across samples (Tipton, Hallberg, Hedges & Chan, 2017; Turner, Paul, Miller & Barbey, 2018), and other statistical issues (Button et al., 2013; Camerer et al., 2018; Kühberger, Fritz & Scherndl, 2014; Simonsohn, 2015; Varoquaux, 2018). In addition, many of the findings from the literature are produced in the context of non-double-blind designs, which create additional methodological difficulties. Coupled with small sample sizes, inadvertent experimenter effects may lead to the perfect conditions for false findings (see Gilder & Heerey, 2018; Ioannidis, 2019; Ioannidis, 2008; Mayer, 2019; Stevens, 2017; Trafimow & Earp, 2016). Finally, many of these tasks are subject to other methodological critiques, including poor re-test reliability, biased task stimuli, and incorrect operationalization of the constructs (Baker et al., 2013; Cribb et al., 2016; Jaswal & Akhtar, 2019; Muth et al., 2014; Schutte et al., 2017).

A third possibility exists for why the present results were not successful at replicating past results. Specifically, it is possible that the failure to find differences in the general population on these tasks is because I have used the wrong models when considering ASD. In this dissertation, and consistent with previous work (e.g., Constantino, 2011; Horder et al., 2014; Ingersoll, 2010; Jones et al., 2013; Sevgi et al., 2020; Trikalinos et al., 2006), I used a spectrum model of ASD as the framework for predictions and questions. While I did this based on the current literature, perhaps this was unwise, and I should have recruited a sample with clinically confirmed ASD diagnoses. That is, it is certainly possible that individuals who are diagnosed with ASD are qualitatively different from those who merely endorse ASD-traits in the general population. Additionally, literature suggests the presence of a great deal of heterogeneity in ASD profiles/causes (Happé & Frith, 2020; Lenroot & Yeung, 2013; Masi, DeMayo, Glozier & Guastella, 2017). If this is the case, then the tasks that are often used for clinical populations may be inappropriate for general populations studies, as such heterogeneity may be magnified as traits become more sparse.

The fourth and final possibility for my findings is that each of these theories, while provocative and seemingly explanatory, may not be correct. Evidence within each of these literatures suggests the presence of mixed findings, with some groups confirming theoretical predictions and other failing to do so (e.g., Bottini, 2018; Brown et al., 2010; Chevallier et al., 2012; Grinter et al., 2009; Happé & Frith, 2006; Hayward et al., 2018; Hoy et al., 2004; Jaswal & Akhtar, 2019; Muth et al., 2014; Nemeth et al., 2014; Sevgi et al., 2020). Thus, findings generally support the idea that the foundations of ASD are not as clear as proponents of these theoretical positions would like.

In addition to these limitations, there is also a caveat associated with the assessment of autism traits within this work. Specifically, a common critique of the AQ is that it has poor internal consistency. Even though the internal consistency of the AQ in the present samples is similar to that reported in previous studies, it is still somewhat low compared to traditional standards within the assessment domain (Hoekstra et al., 2008; Hurst et al., 2007; Streiner, 2003; Wakabayashi et al., 2006).

Another limitation in this work relates to the decision to use a median split strategy for most of the analyses. Although the goal of using this analytic strategy was to make these results comparable to the literature, in which a median split strategy is common, splitting the samples does reduce statistical power. In addition, it is not consistent with the idea of the spectrum model of autism introduced at the beginning of this document, potentially obscuring significant results with smaller effect sizes within the sample. Regardless, a number of other more nuanced exploratory analyses (e.g., regression analyses, Bayesian analyses) were conducted during this work that were not included in this document suggest that the fact that I found mainly null results does not lie solely in the analytic strategy.

Lastly, an important aspect of this work that is both a limitation and a strength lies in my choice to use a general population sample. Although the benefits of using this sample were discussed earlier in the document, I now address some limitations to my sampling strategy as well. For example, although I did recruit from the general population of the London Ontario area, the majority of participants were undergraduate psychology students. This fact limits the generalizability of results much beyond this group. Second, without access to a clinical population, it is difficult to make conclusions about how these findings might apply to diagnosed individuals. It might be the case that a properly powered and double blinded study involving diagnosed individuals would have shown results even though the present samples did not have the sensitivity to detect differences. Thus, these conclusions should only be generalized beyond the sample with caution.

6.6 Future Directions

One important area that future research should examine is the idea that ASD-related traits affect social behavior. Specifically, the participants in this work only interacted with one person. It might be the case that more subtle differences would emerge if interactions could have been repeated with multiple partners or with friends as well as strangers. Additionally, due to time constraints, the current dissertation was limited to looking only at the social behavior of one partner. In the future, research should look at the integrated behaviors of both social partners, and how a participant's behavior at one time-point within an interaction might predict their partner's behavior at time two. This would provide the ability to provide a real understanding of how people sequence social behavior across time and where the behaviors of individuals with high levels of ASD-traits diverge from expected patterns.

Second, for proponents of any of the theories discussed in this dissertation, these data should be a call to replicate previous findings in large, double-blind samples to provide support for theoretical claims. Additionally, work should be conducted to demonstrate an association between predicted cognitive/motivational differences and real-life outcomes. Previous research has made many claims and assumptions about how in-lab findings will translate into real-life social outcomes but almost none have tested this. Rather than merely providing theoretical linkage between ASD theory and social behavior, researchers should seek to describe the empirical relationships between their tasks and naturalistic social behavior. Although the current dissertations findings are limited in that they did take place in a lab, the social findings were from an unscripted, highly naturalistic 'get-to-know-you' type interaction. Data from all the tasks did not seem to correlate with social outcomes although the one study that included both social behavior and task performance did show the anticipated behavioral associations. Additional data related to this linkage would certainly be helpful in understanding task outcomes.

6.7 Conclusion

The current dissertation has generated important support for the concept that ASD related traits affect social behavior across the general population in predictable ways, thereby supporting the idea of a spectrum-based model. Although the aim of this project at its beginning was to add nuance to the set of deficits, both social and social cognitive, within the ASD spectrum, it has instead produced many findings that add to a growing pool of literature that critiques the social motivation, central coherence, and probabilistic learning theories of ASD. Finally, this dissertation emphasizes the importance of collecting well-powered and double-blinded studies, whenever possible. Thus, the conclusion from these data may be that more robust theoretical tests are long overdue in the field of autism research.

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Appendix A: Ethics Approval Forms

Date: 6 November 2017

To: Dr. Erin Heerey

Project ID: 110039

Study Title: Associative Learning of Social Cues

Application Type: NMREB Initial Application

Review Type: Delegated

Full Board Reporting Date: 08/Dec/2017

Date Approval Issued: 06/Nov/2017 15:21

REB Approval Expiry Date: 06/Nov/2018

Dear Dr. Erin Heerey

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the above mentioned study, as of the date noted above. NMREB approval for this study remains valid until the expiry date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

This research study is to be conducted by the investigator noted above. All other required institutional approvals must also be obtained prior to the conduct of the study.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
AllQuestionnaires	Other Data Collection Instruments	07/Sep/2017	1
Debrief_StudyVer1	Debriefing document	07/Sep/2017	1
LetterOfInformation_Ver1	Implied Consent/Assent	07/Sep/2017	1
SONA_AdvertVer1	Recruitment Materials	07/Sep/2017	1
Stimuli	Other Data Collection Instruments	07/Sep/2017	1

Documents Acknowledged:

Document Name	Document Type	Document Date	Document Version
Counterbalancing	Supplementary Tables/Figures	07/Sep/2017	1

No deviations from, or changes to the protocol should be initiated without prior written approval from the NMREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Katelyn Harris, Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

Western Research

Date: 20 September 2018

To: Dr. Erin Heerey

Project ID: 111158

Study Title: A Study of Social Cognition and Learning 2

Application Type: NMREB Amendment Form

Review Type: Delegated

Full Board Reporting Date: 05/Oct/2018

Date Approval Issued: 19/Sep/2018 16:14 20/Sep/2018 11:35

REB Approval Expiry Date: 07/Feb/2019

Dear Dr. Erin Heerey,

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the amendment, as of the date noted above.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
AllQuestionnaires_Cleaned	Other Materials	30/Aug/2018	2
SCL_Debrief_Form_Cleaned	Recruitment Materials	30/Aug/2018	2
SCL_LOI_Cleaned	Implied Consent/Assent	30/Aug/2018	2
SONA_Advert_Cleaned	Recruitment Materials	30/Aug/2018	2
Stimuli	Other Data Collection Instruments	30/Aug/2018	1

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Katelyn Harris, Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Western Research

Date: 2 August 2019

To: Dr. Erin Heerey

Project ID: 114304

Study Title: Cognition and Social Behaviour

Short Title: Cognition and Social Behaviour

Application Type: NMREB Initial Application

Review Type: Delegated

Full Board Reporting Date: September 6 2019

Date Approval Issued: 02/Aug/2019

REB Approval Expiry Date: 02/Aug/2020

Dear Dr. Erin Heerey

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the above mentioned study, as of the date noted above. NMREB approval for this study remains valid until the expiry date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

This research study is to be conducted by the investigator noted above. All other required institutional approvals must also be obtained prior to the conduct of the study.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
AllQuestionnaires	Paper Survey	01/Jul/2019	1
Debrief_Form	Debriefing document	01/Jul/2019	1
Flyer for Local Processing Study	Recruitment Materials	01/Aug/2019	2
Leuven Embedded Figures Test Stimuli	Other Data Collection Instruments	01/Jul/2019	1
LOI_PAID	Implied Consent/Assent	01/Jul/2019	1
LOI_SONA	Implied Consent/Assent	01/Jul/2019	1
SONA_Advert	Recruitment Materials	01/Jul/2019	1

No deviations from, or changes to the protocol should be initiated without prior written approval from the NMREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Kelly Patterson, Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Appendix B: Power Analyses

Reward Sensitivity Task

Previous research that uses this task (or a modified version of it), reports medium to large effect sizes (η^2: .12 - .46; Pizzagalli, Jahn, & O'Shea, 2005). To obtain 95% power using a conservative estimate of medium effect size and at the standard .05 alpha error probability, G*Power (Faul, Erdfelder, Buchner & Lang, 2009) estimates a sample of 88 per group (176 in total).

Smile Valuation Task

This task did not receive a power analysis as it was a secondary analysis on a set of data and an a priori estimate of effect size was not made.

Leuven-Embedded Figures Task

For this task we ran an a-priori power analysis. Previous research has shown learning differences between individuals classified as endorsing high levels of ASD traits on the AQ and those endorsing low ASD-trait levels. Using an embedded figures task, research suggests a Cohen's d of .759 for error rate performance, and .973 for response time performance (Cribb, Olaithe, Di Lorenzo, Dunlop & Maybery, 2016). As I was testing both, I used the more conservative estimate. To obtain 95% power with an estimated effect size of .759 and at the standard .05 alpha error probability, G*Power (Faul, Erdfelder, Buchner & Lang, 2009) estimates a sample of 39 per group. However, because it is likely that this effect size overestimates the true effect, I opted to increase the desired sample size to 200 participants (100 per group).

Probabilistic Selection Task (Replication)

For this task we ran an a-priori power analysis. Using a similar probabilistic selection task as my own, research suggests a Cohen's d of .41 (Solomon et al., 2011). To obtain 95% power with an estimated effect size of .4 and at the standard .05 alpha error probability, G*Power (Faul et al., 2009) estimates a sample of 136 per group. However, because it is likely that this effect size overestimates the true effect, I opted to increase the desired sample size to 300 participants (150 per group).

Associative Learning Task

For this task we ran an a-priori power analysis. Using an associative learning task, much like the one I used in this dissertation, research suggests at least a medium effect size (Sevgi et al., 2020). To obtain 95% power with an estimated effect size of .5 and at the standard .05 alpha error probability, G*Power (Faul et al., 2009) estimates a sample of 88 per group. However, because it is likely that this effect size overestimates the true effect, I opted to increase the desired sample size to 200 participants (100 per group).

Appendix C: Chapter 3 MSCS Descriptive Statistics Table

Table C1. *Demographic Information for high and low social competency groups*

MSCS Group	Low MSCS (MSCS ≤ 286)	High MSCS (MSCS > 286)	*F*	*df*	*p*
n	107	96			
Score Range	209-286	287-346			
Sex (Female:Male) *	76:31	80:16	4.31	1,201	.038
Age in years	20.2 (4.4)	21.2 (9.2)	1.02	1,201	.314
Autism-spectrum Quotient					
Total Score	23.19 (5.7)	16.4 (4.7)	85.46	1,202	<.001
Social Skills	4.7 (2.4)	2.0 (1.7)	87.45	1,202	<.001
Attention Shifting	6.1 (1.8)	4.6 (2.1)	28.00	1,202	<.001
Attention to Detail	5.6 (2.2)	6.0 (2.0)	1.92	1,202	.167
Communication	3.7 (1.9)	1.6 (1.5)	76.77	1,202	<.001
Imagination	3.0 (1.8)	2.2 (1.5)	15.17	1,202	<.001
Big Five Inventory					
Extraversion	34.4 (9.7)	26. 6 (8.4)	36.42	1,202	<.001
Agreeableness	29.4 (7.4)	22.3 (6.1)	54.46	1,202	<.001
Conscientiousness	32.3 (7.4)	25.5 (7.1)	44.30	1,202	<.001
Neuroticism	27.6 (8.8)	33.3 (8.7)	21.59	1,202	<.001
Openness	34.7 (8.1)	31.3 (8.9)	8.09	1,202	.005
Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS)					
BIS	22.5 (3.3)	22.3 (3.6)	0.10	1,202	.753
Fun Seeking	11.7 (2.4)	12.6 (2.1)	7.32	1,202	.007
Drive	11.0 (2.3)	11.4 (2.7)	1.35	1,202	.247
Reward Responsiveness	17.5 (1.6)	18.2 (1.7)	8.03	1,202	.005
Multidimensional Self Concept Scale (MSCS)					
Total	263.8 (16.4)	310.5 (16.5)	406.93	1,202	<.001
Social Motivation	34.2 (6.3)	42.7 (5.8)	99.29	1,202	<.001
Demonstrating Empathetic Concern	40.6 (5.9)	47.5 (4.6)	148.39	1,202	<.001
Nonverbal Sending Skills	38.6 (5.8)	45.8 (4.7)	85.70	1,202	<.001
Social Inferencing	37.2 (2.5)	44.8 (3.9)	104.86	1,202	<.001
Social Knowledge	43.6 (4.6)	49.2 (3.1)	40.84	1,202	<.001
Verbal Conversation Skills	35.8 (5.1)	40.6 (5.7)	99.43	1,202	<.001
Emotion Regulation	34.1 (6.3)	39.9 (5.5)	48.41	1,202	<.001
Reading the Mind In the Eyes Task (RMET)					
Total Score	24.7 (4.7)	27.0 (4.2)	13.06	1,202	<.001
Letter Number Sequence Task (LNS)					
Total Score	14.5 (4.6)	14.8 (4.2)	0.31	1,202	.578

Note. Table reports means (SDs in parentheses) and comparison test statistics. Comparisons tested with ANOVA except where noted. 1 participant did not report their ages; 1 did not report sex information. * Comparison tested with Chi-Squared.

Appendix D: Associative Learning Task Additional Analyses

This is the analysis to determine if participants performed above chance on the associative learning task. As reported in the table below, participants performed statistically above chance on the associative learning task. See Table D1 and Figure D1 for more details.

Table D1. *Exact t-test results for performance compared to chance*

Variable	df	*t*	*p*
Low AQ			
Nonsocial Advice			
Trials 1-30	112	11.31	<.001
Trials 31-70	112	6.48	<.001
Trials 71-120	112	11.06	<.001
Social Advice			
Trials 1-30	112	10.10	<.001
Trials 31-70	112	8.21	<.001
Trials 71-120	112	10.36	<.001
High AQ			
Nonsocial Advice			
Trials 1-30	69	7.61	<.001
Trials 31-70	69	7.35	<.001
Trials 71-120	69	7.82	<.001
Social Advice			
Trials 1-30	69	8.83	<.001
Trials 31-70	69	7.11	<.001
Trials 71-120	69	9.76	<.001

Note. AQ is the Autism-spectrum Quotient. Advice Type refers to whether participants received social or non-social advice during the task.

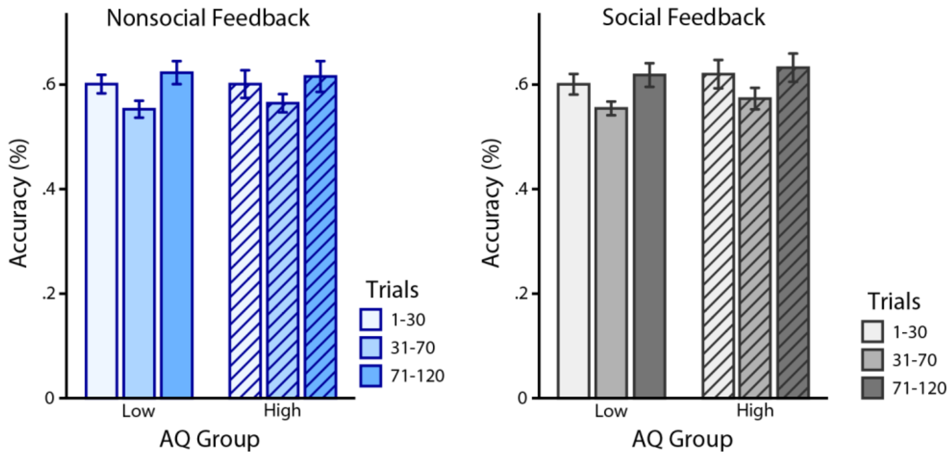

Figure D1. Proportion Correct in the associative learning task.

Curriculum Vitae

Name:	Joshua Patenaude
Post-secondary Education and Degrees:	McMaster University Hamilton, Ontario, Canada 2009-2013 H.B.S.
	Sam Houston State University Huntsville, Texas, USA 2013-2015 M.A.
	The University of Western Ontario London, Ontario, Canada 2015-Present Ph.D.
Honours and Awards:	C. Kingsley Allison Research Grant 2017
Related Work Experience	Teaching Assistant McMaster University 2011-2013
	Teaching Assistant Sam Houston State University 2014-2015
	Teaching Assistant The University of Western Ontario 2015-2020

Publications:
*Indicates shared first authorship

Balakrishnan, A.*, Palma, P. A.*, Patenaude, J.*, & Campbell, L. (2017). A 4-study replication of the moderating effects of greed on socioeconomic status and unethical behaviour. *Scientific data*, *4*, 160120.