Enter the Wild: Autistic Traits and Their Relationship to Mentalizing and Social Interaction in Everyday Life

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Abstract

Theories derived from lab-based research emphasize the importance of mentalizing for social interaction and propose a link between mentalizing, autistic traits, and social behavior. We took social cognitive research outside the lab to test these assumptions in everyday life. Via smartphone-based experience sampling and logging of smartphone usage behavior we quantified mentalizing and social interaction in our participants' natural environment. Both measures were compared with autistic traits, controlling for Big Five personality dimensions, social anxiety, and verbal intelligence. Mentalizing occurred less frequently than reasoning about actions and participants preferred to mentalize when alone. Autistic traits were negatively correlated with communication via smartphone. Yet, they were not associated with social media usage, a more indirect way of getting in touch with others. We further found no relation between autistic traits and social network size. These findings critically inform recent theories on social cognition and behavior in individuals with and without autism.

Keywords: Autism, Experience Sampling Method, Mentalizing, Mobile Sensing, Theory of Mind

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"Why is she not texting me back?" A large part of our everyday social life consists of trying to answer questions like this to make sense of other's behavior. Mentalizing is a powerful cognitive tool to explain and predict behavior. It is the ability to impute mental states such as beliefs, desires or intentions to others and ourselves. Mentalizing is considered essential for social interaction.

Theories on the cognitive basis of autism spectrum conditions (hereafter "autism") are in line with this view by suggesting a causal link between altered social cognitive information processing and reciprocal social interaction and communication in autism (Frith, 2012; Tager-Flusberg, 1999). The autism spectrum is characterized by a set of autistic traits, such as problems with balanced and reciprocal social interaction, rigid behavior patterns, difficulties in adapting to change, strong attention to details, or a strong focus of attention (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001; Hurley, Losh, Parlier, Reznick, & Piven, 2007). People who meet criteria for an autism diagnosis are considered being at the extreme end of this spectrum (American Psychiatric Association, 2013). Relatives of autistic people also show an increased –yet subclinical– level of autistic traits (Sasson et al., 2013). However, autistic traits are also continuously distributed in the general population (Ruzich et al., 2015).

To date, central pillars of theories suggesting the importance of mentalizing for everyday social interaction and a link between mentalizing, autistic traits, and actual social behavior remain under-researched. On the one hand, our knowledge about mentalizing in people with and without autism stems almost exclusively from lab-based research (c.f., Atherton, Lummis, Day, & Cross, 2018). On the other hand, social interaction outside the lab is usually assessed indirectly via interviews or questionnaires (e.g., Kreider et al., 2016). Only a handful of studies have addressed the impact of social cognitive deficits of individuals with autism on their everyday social life (Atherton et al., 2018; e.g., Begeer, Malle, Nieuwland, & Keysar, 2010; Chen, Bundy, Cordier, Chien, & Einfeld, 2016; Frith, Happé, & Siddons, 1994). Consequently, there is a large gap between the solid empirical basis of mentalizing characteristics in the lab and knowledge about actual social interaction in everyday lives of people with and without autism. Central questions that remain unanswered are: When and how do we mentalize? Is there a relationship between autistic traits and the amount and quality of mentalizing, the amount of social interaction, and more generally the extent of exposure to the social world and social network size in everyday life?

In this study, we assessed autistic traits, social cognitive processing in everyday life, and actual social behavior. The conceptualization of autism as a dimensional condition and the prevalence of autistic traits in the general population, made it possible to address the questions above in a non-autistic sample (Landry & Chouinard, 2016). Our strategy was two-fold: First, we employed the experience sampling method (ESM), a way to capture moment-to-moment cognitive processing in an everyday context (Hektner, Schmidt, & Csikszentmihalyi, 2007), to measure the amount and quality of mentalizing outside the lab. Second, we measured the amount of communication and exposure to the social world via logging of smartphone usage behavior. Both measures were then compared with the participant's level of autistic traits, controlled for Big Five personality dimensions, social anxiety, and verbal intelligence.

One other study previously used ESM to quantify the extent to which we mentalize. Bryant et al. (2013) sampled thoughts of 30 participants during a period of 10 hours. They categorized whether their participants were thinking about mental states, actions, or something else. The main finding was that overall, adults think more about actions than about mental states. However, this pattern was context-sensitive: they thought more about actions than mental states when they were interacting, but more about mental states than actions when they were alone.

In the present study, participants answered ESM surveys over a period of 30 days via their smartphones. First, we aimed to replicate Bryant et al.'s (2013) findings in a larger sample over a longer sampling period. Second, we added new categories that are crucial to understanding what mentalizing is used for in everyday life. Specifically, we were able to investigate whether their mental state thought referred to the past, present, or future, and whether it referred more to themselves, someone else, or both. Third, derived from the notion that autism is associated with a reduced use of mentalizing (cf., Frith et al., 1994), we hypothesized a negative relationship between autistic traits and the overall amount of mental state thoughts (but, see Begeer et al., 2010). Further, although previous research showed that people with autism are interested in social interactions and do experience loneliness when this desire is not sufficiently satisfied (Howard, Cohn, & Orsmond, 2006; Locke, Ishijima, Kasari, & London, 2010), it has been speculated that people with autism find social interactions little rewarding and that they have a diminished motivation to engage with others (Chevallier, Kohls, Troiani, Brodkin, & Schultz, 2012). If this were the case, we would expect to find an association between autistic traits and the emotional valence experienced while cognitively engaging with the social world.

In the second part of our study, we investigated links between autistic traits and actual social interaction in everyday life. To this end, we tracked our participants' smartphone usage behavior. Doing this we made use of the facts that today (1) a main purpose of smartphones is to communicate, and (2) smartphones are ubiquitous and record an abundance of our everyday life behavior. Therefore, smartphone usage profiles can be used to study links between psychological phenomena and behavior in an ecologically valid and non-disruptive way (Miller, 2012; Stachl et al., 2017).

Results from initial studies remain ambiguos about the extent to which people with autism use electronic devices to get in touch with the social world (Mazurek, 2013; Mazurek, Shattuck, Wagner, & Cooper, 2012; van Schalkwyk et al., 2017). In contrast to this previous work, we did not have to rely on indirect questionnaire data. Moreover, we were able to distinguish between communication (e.g., using a messaging app) and social media usage, a way to connect to the social world without the need to directly communicate. Considering that maintaining reciprocity in interaction is challenging in autism, the former might be particularly difficult for people with high autistic traits, whereas the latter might provide a low-threshold opportunity to participate in social life.

We hypothesized that an association between autistic traits and the amount of everyday life communication via smartphone should become evident in a negative relationship between autistic traits and the amount our participants used their smartphones to communicate. Further, if autistic traits are related to a reduced participation in the social world (Mazurek et al., 2012), we should find a negative relationship between autistic traits and social media app usage. Finally, based on previous findings on smaller social network sizes in people with autism (Kreider et al., 2016), we hypothesized that the level of autistic traits should be negatively correlated with the number of contacts saved on the participants' smartphone.

Method

The pre-registrtaion, material and data of this study can be found at OSF (https://osf.io/39tvf/). We report how we determined the sample size, all data exclusions, all manipulations, and all measures in this study. For the sake of brevity, deviations from the pre-registration protocol are described in the Supplemental Material. The demographic information is not shared as it cannot be guaranteed that it is impossible to identify individual data sets.

Participants

In total, 234 adults (51% female) between the age of 18 and 50 years of age (M = 22.70, SD = 3.85) took part in this study. They were mainly recruited via university mailing lists and campus bulletins. The participants received €25 for their participation. If they managed to complete 50 out of 60 ESM surveys, they received an extra €1 for each additionally filled survey (max. €35). They further took part in a lottery to win a smartphone or tablet worth €400. On average, the participants answered 41 surveys (SD = 9). The ethics committee of the Department of Psychology and Education of LMU Munich approved this study. Participants were included if they used an Android smartphone and reported no history of psychiatric or neurological condition. In the debriefing questionnaire, $n = 0$ participants reported that they were aware of a family member with autism. German native speakers or people with equivalent language skills could participate in the study. Forty-three additional adults signed up for the study but had to be excluded because they did not show up for the post-sampling lab appointment ($n = 14$), they had technical problems with the application on their smartphone ($n = 18$), the data was lost irrecoverably (e.g., the smartphone broke, $n = 5$), they neither filled enough ESM surveys nor enough smartphone usage data was sampled ($n = 6$, criteria below). Data collection started in August 2016 and ended in August 2017.

The participants (74% were currently enrolled students) stem from various fields of studies or occupation (40% social/medical, 25% mathematics/physics/engineering, 7% humanities, 3% law, 12% business/economics, 0.43% arts, 1% multiple subjects/occupations, 12% other). A total of 64% held a secondary degree, 34% held a postsecondary degree, and 2% had other degrees. A list of the participant's smartphone types and Android versions can be found at the OSF.

The sample size was determined based on an *a priori* power analysis. For a weak correlation ($r = 0.2$), with α (two-tailed) set to 0.05 and (1-β) set to 0.8, a minimum of 193 participants were required. For the analysis of the ESM surveys, and of the smartphone usage behavior analysis, we ended up with two different - yet largely overlapping - subsamples ($n = 220$ for the ESM analysis and $n = 223$ for the smartphone usage data analysis). In some cases, we received data for one, but not the other analysis (e.g., if a participant did not fill enough ESM surveys, but sufficient smartphone usage data was collected). The analyses of the ESM data and the smartphone usage data were run with the respective subsample.

Measures and Analysis

Autistic Traits Questionnaires. We assessed the level of autistic traits via the three most commonly used and validated self-report questionnaires. These questionnaires sensitively assess the prevalence of autistic traits in the general population, each one tapping into slightly different aspects of autistic personality traits. For the analyses in this study, individual scores in these three questionnaires were combined in a single compound score of autistic traits (mean of z-transformed scores of each questionnaire). All questionnaires (including the control questionnaires) were filled via PCs in the lab.

Autism-Spectrum Quotient. The *Autism-Spectrum Quotient* (AQ; Baron-Cohen et al., 2001) is a 50-item self-report questionnaire that measures the level of autism-associated traits in the five subscales *social skills*, *attention switching*, *attention to detail*, *communication*, *imagination*. The sum score ranges between 0 and 50 (the higher the score, the more autistic traits were reported). In a meta-analysis, Ruzich et al. (2015) showed that AQ scores are continuously distributed in the general population. In a typical nonclinical sample, the mean score is approximately 17 (*SD* range: 0.8-9.7). For this study, we used a German adaption (Freitag et al., 2007).

Empathy Quotient. The *Empathy Quotient* (EQ; Baron-Cohen & Wheelwright, 2004) assesses cognitive and affective aspects of empathic traits with 40 items. A high EQ score (range: 0-80) indicates a high level of empathy. Previous research showed that individuals with autism score significantly lower in the EQ than individuals without autism (Baron-Cohen & Wheelwright, 2004). Baron-Cohen and Wheelright reported a mean EQ score of 42.1 ($SD = 10.6$) in a general population sample. On average, women score higher than men. We employed the German translation retrieved from http://www.autismresearchcentre.com/arc_tests. For the calculation of the compound score we reverse scored z-transformed EQ scores.

Broader Autism Phenotype. The broader autism phenotype questionnaire (BAP; Hurley et al., 2007) measures a set of personality traits and language characteristics that are qualitatively similar to core symptoms of autism. It was initially developed to assess the prevalence of these characteristics in families of people with autism. The BAP consists of 36 items and the three subscales *aloof* (lack of interest/joy in social interactions), *rigid* (change aversion) and *pragmatic* (communication difficulties due to deviations in social aspects of language use). A mean score is calculated for each subscale and over all items. In the study by Hurley and colleagues, the general population sample had a mean total score of 2.74 ($SD = 0.55$). The German version created for this study can be found at the OSF.

Control Questionnaires. To ensure that possible effects can be attributed to the variation in autistic traits, and not to other potentially confounding factors, we assessed several control measures.

Social Interaction Anxiety and Social Phobia. Social anxiety and social phobia are highly prevalent comorbidities of autism (MacNeil, Lopes, & Minnes, 2009).

Further, these are also strongly related phenomena in the general population (Liew, Thevaraja, Hong, & Magiati, 2015). Yet, a recent study also reported differential effects of social anxiety and autistic traits on social attention, suggesting that these phenomena might be - at least partly - distinct (Kleberg et al., 2017). In this study, we included the *Social Interaction Anxiety Scale* and the *Social Phobia Scale* (SIAS and SPS respectively; Mattick & Clarke, 1998; German version by Stangier, Heidenreich, Berardi, Ulrike, & Hoyer, 1999) to identify the variance that is attributable to social interaction, anxiety, and social phobia. Mattick et al. reported a mean SPS score of 14.1 (SD = 10.2), and a mean SIAS score of 19.0 (SD = 10.1) in an undergraduate sample.

Verbal Intelligence. We employed a German multiple choice vocabulary test as a rough estimate of verbal intelligence (*Mehrfachwahl-Wortschatz-Intelligenztest*, MWT-B; Lehrl (2005)). The aim was to control for a potential influence of verbal intelligence on performance in our measures of interest (ESM and smartphone usage data), which are both inherently language-dependent.

Big Five Personality. The German version of the Big Five Structure Inventory was employed to obtain Big Five personality scores (BFSI; Arendasy, 2009). We used the person parameter of the partial credit model (PCM; see Masters, 1982). The self-report questionnaire consists of 300 items. The participants are asked to evaluate how typically/untypically an adjective or a short phrase describes how they are. The response is provided using a four-point Likert scale ranging from *untypical for me* to *typical for me.* The Big Five personality dimensions (*Openness to Experience, Conscientiousness, Extraversion*, *Emotional Stability*/Absence of *Neuroticism*, and *Agreeableness*) are measured on the factor- and the facet-level.

Debriefing Questionnaire. A short debriefing questionnaire, completed by the participants at the end of the study, assessed (1) the pleasantness of study participation, (2) how difficult it was to identify the respective thoughts for the ESM surveys, (3) whether the participant's daily life during the study was typical or not, (4) if, and if so how, the study had an influence on the way they used their smartphone, and (5) how many hours a day they usually interact with others (face-to-face and via technical devices).

Experience Sampling Method. We integrated an ESM extension into an already existing version of the *PhoneStudy* Android logging application (made available for Android 4.0 or higher; see also Stachl et al., 2017). The participants completed 60 surveys in 30 days. The timing of the surveys was pseudo-randomized and unpredictable for the participants. The participants were instructed that, on average, they will receive 2 (0-4) surveys per day, and that the surveys will only be scheduled between 10am and 8pm. A status screen, accessible via the navigation drawer, informed the participants how many surveys they already completed, and on how many surveys they will receive this day. Participants who completed less than 33% of the ESM surveys (20 out of 60), were excluded from the analysis.

The current ESM measure was closely adapted from a study by Bryant and colleagues (2013). All 60 surveys were identical and consisted of five multiple-choice questions in a fixed sequence. The first question referred to the type of thought: "What were you thinking of just before the beep?" (response options: mental state/action/miscellaneous/I cannot tell exactly right now). The second question asked about the direction of the thought: "Who was involved in this thought?" (response options: I/someone else/I and someone else/miscellaneous/i cannot tell exactly right now). The third question addressed the time reference of the thought: "What was the timeline of the thought?" (response options: past/present/future/none of these options). The fourth question referred to the participant's mood while thinking this thought: "How did you feel while having this thought?" (response options: pleasant/neutral/unpleasant/I cannot tell exactly right now). The fifth question asked whether participants were interacting while having the thought: "Were you engaged with others while having this thought?" (response options: yes/no).

The ESM surveys popped up as visual notifications on the lock screen, accompanied by a beep and a haptic feedback (vibration). To answer the survey, participants had to touch the notification. Once opened, they had 10 min to fill the survey, after that the notification disappeared and the survey was counted as missed. Participants were instructed to answer as many surveys as promptly as possible, without putting themselves in danger by doing so (e.g., if they were currently driving). At the beginning of the study, the participants completed a standardized instruction and training, implemented in the *PhoneStudy* app (for details see material at OSF). In a standardized step-by-step procedure, the application instructed the participants on how to adequately respond to the ESM promts. For example, for the first question on the type of thought, it was crucial to explain the meaning of the terms *mental state* and *action*. The participants were instructed that mental states only exist in their or another person's head. Examples for mental states are opinions, beliefs, desires, or feelings. An *action* was defined as something that they or others are doing. All definitions were accompanied by examples (e.g., I think Sarah is still at work, I will brush my teeth before I go to bed). The other questions were explained accordingly (see OSF for details). A potential disadvantage of fixed response categories as compared to free text responses could be a wrong or imprecise categorization of the thought of interest. Yet, comparing both response formats, Bryant et al. (2013) found the same pattern of results. Based on cost-effectiveness considerations and the difficulty to unambiguously categorize free text, we decided to use multiple-choice responses.

Following the instruction, the participants completed a training session (referred to as "quiz" in the app). It consisted of 36 example thoughts that had to be categorized correctly (4 question types * 9 example thoughts). For example, the thought "I want to eat chocolate although I shouldn't" had to be categorized correctly as mental state that refers to the participant him- or herself and to the present. For the question addressing the participant's mood, any option was counted as correct. The training session was only passed if all questions were answered correctly. Incorrectly answered questions were repeated until the correct response was provided. Throughout the whole test period, the instruction and the training were available via the navigation drawer.

At the end of the study, participants provided feedback about the ESM methodology in a short debriefing questionnaire. In the current sample, 17% rated the ESM procedure as pleasant, 73% as neither pleasant nor unpleasant, and 10% as unpleasant. The debriefing questionnaire showed that participants were sufficiently able to identify a respective thought (7% always, 73% most of time, and 20% half of the time). Note that the participants were instructed to select the option "I cannot tell exactly right now" in situations in which they were not able to unambiguously identify a respective thought.

Social Interaction via Smartphone. Smartphone usage behavior was automatically recorded via the *PhoneStudy* Android mobile sensing application (Stachl et al., 2017). The app uses background services to monitor a wide range of smartphone usage behavior, such as app usage, communication (calls, SMSs), mobility assessed via geolocation, listened music tracks, Bluetooth/Wifi connections, battery-charging events, and boot events. For the planned analyses of the current study, we focussed on the following variables as indicators of social interaction via smartphone: number and duration of incoming and outgoing calls, number and total length of received and sent SMSs, and number and duration of events in which participants used apps for social interaction (e.g., WhatsApp, Facebook, Twitter, etc.). Further, the number of contacts at the end of the logging period was recorded as an indicator of social network size. The *PhoneStudy* app neither tracks the content of written text nor does it record spoken words. Contacts are hashed. In a first anonymization step, we assured that personal information and logged data are never jointly stored. After the second anonymization step, neither the experimenters nor the participants were able to link personal information to a data set. Because the collected raw data is still sensitive (e.g. via geolocation in combination with the usage of certain apps), the possibility that a person could be identified cannot be excluded. Therefore, we saved this data inaccessible to the public, adhering to data storage guidelines of the local university.

The smartphone usage events were logged as a list of timestamp-sorted actions. Each event was a row that contained information about the time of the event (e.g., "1488966198449"), geolocation (e.g., "48.156024, 11.582928"), application name (e.g., "WhatsApp"), and package name (e.g., "com.whatsapp"). The service assessed the currently running app every two seconds, creating a log entry if it had changed. Devices operating on newer versions of the Android operating system supported reading the app usage history directly. On capable devices, our app thus automatically switched to this method, retrieving the latest history every 15 minutes. The participants were instructed to regularly transfer the collected data to our server, using SSL encryption. Additionally, the final database was automatically transferred to the server once the logging period ended.

In a first processing step, we filtered out events that did not reflect usage behavior. These events were produced by apps that run in the background and are not voluntarily controlled by the participant (e.g., the launch and functioning of a manufacturer-specific keyboard). Those background apps vary between manufacturer types and Android versions. A list of all filtered background apps that were at work in the current sample can be found at the OSF. Subsequently, we identified and categorized usage events of apps for social interaction. Due to the multitude of relevant apps and because some apps could not be unambiguously categorized whether they are used for social interaction or not, we had to individually decide in which category an app fitted best. A source for these decisions were descriptions of the applications' purpose that are available at the Google Play Store.

For our analyses, we formed two categories which served as dependent variables (a list of apps per category can be found at the OSF). The first category, termed *communication*, subsumed events of apps with the main purpose to communicate with others verbally or via text messages. These events were generated by pre-installed apps for phone calls and messaging, as well as by apps from other providers (e.g., WhatsApp, Signal, or Skype). For this analysis, we made no distinction between verbal communication and text messaging, because many of these apps offer both communication forms and this could not be differentiated in the logged event. We did not consider e-mail apps for this category. First, because a substantial amount of e-mail traffic is related to contacting companies or agencies (e.g., for online shopping). Second, because the amount of work-related e-mails, a rather involuntary form of communication, could not be identified for filtering them out.

The second category, termed *social media usage*, grouped events of apps that connected the participants to the social world without the need to directly communicate. Although messaging can be a feature of these apps, the main reason to us these apps is not communication. Apps for classical social networks such as Facebook or Instagram are in this category. An important reason to use such an app is to address one's need to belong and/or one's need to self-represent (Nadkarni & Hofmann, 2012). Further, browsing one's timeline can merely be used to gather news on individually-relevant topics. Another type of apps in this category is used to coordinate group tasks (e.g., shared calendars, apps that help to share costs between several people, or apps that can be used to manage a sports team). Dating apps were also included in this category. Although communication takes place in dating apps, their main purpose is to look at other people's profiles in order to find a matching person.

In the next processing step, the total number of events per app and category was calculated. Further, the total usage duration of apps of the two categories was calculated. This was done by computing the difference between the timestamp of an event of interest (e.g., the first occurence of a "WhatsApp" usage event) and the timestamp of the next event generated by the usage of a different app or operation (e.g., turning the screen off). Ten participants had to be excluded because usage data was missing for more than 3 days of their logging period. For nine participants, logging data was missing for less than 3 days. For these participants, we interpolated the number and duration of usage per app (via the rule of three, in total 0.17% of the data) to match the logging period of exactly 30 days. This criterion was set during data preprocessing, prior to data analysis.

Due to a logging issue, a systematic error was introduced to the number and duration of app usage events. In some situations, it was not logged when a participant turned off her screen, which led to implausibly long app usage events. For example, if a participant used Whatsapp before she went to bed and the event of turning off the screen was not logged, the whole time until the next event in the morning (e.g., alarm clock) was incorrectly counted as duration of WhatsApp usage. As the occurence of this logging error was related to the amount our participants used their smartphone, a simple exclusion of these events would have biased our data set. To solve this issue, we identified these events in the raw data and replaced them with the participant's mean usage duration of this app. The number of logging error events was added to the recorded total number of usage events per app. Thus, the total number of app usage events could be accurately reconstructed. For the total duration of communication events, 9.07% of the data was interpolated. For the variable total duration of social media usage, 2.33% of the data was interpolated. Aggregated data before and after this correction is available at the OSF.

All data processing and analyses were performed with statistical software R 3.5.0 (R Core Team, 2018). A full list of employed packages can be found at OSF.

Procedure

The study was comprised of three parts. First, participants were invited to a pre-sampling lab appointment (based on the participant's schedule, those were individual or group sessions). In the morning of the same day, they received instructions via mail on how to install the app. At the beginning of the lab appointment, the experimenter made sure that everyone successfully installed the app and provided help if necessary. Subsequently, participants completed the standardized ESM instruction and training. The experimenters answered any upcoming questions. After that, the participants completed the verbal intelligence questionnaire and the BFSI[1] on a PC. The ESM period started one day after the first lab appointment. During the following 30 days, which constituted the second part of the study, the participants received the 60 ESM surveys. During the same time, their smartphone usage behavior was recorded. For the third part, the participants were invited to

[1]Note that half of the participants filled the BFSI at the post-sampling lab appointment. Further, all participants additionally completed the BFSI on their smartphone either at the beginning or the end of the 30 days. This data was used for an independent study: https://osf.io/h9pdb.

a post-sampling lab appointment, in which they filled the autistic trait questionnaires, the social interaction anxiety, and social phobia questionnaires on a PC. Additionally, they completed the debriefing protocol (a paper-and-pencil version). Finally, they received their reimbursement, based on the amount of filled ESM surveys.

Results

All confirmatory partial correlations on the relationship between the level of autistic traits and the other measures of interest (ESM surveys and smartphone usage behavior) were corrected for multiple comparisons using the Holm-Bonferroni adjustment. For all computed t-tests, Hedges g was used as a measure of effect size.

Autistic traits, control measures and debriefing

Table 1 provides descriptive statistics of the questionnaire results. The means and standard deviations of the current sample are highly comparable to those reported for the general population in previous literature. In the debriefing questionnaire, the participants indicated that they usually interact with others for about 7.05 hours per day (face-to-face and via technical devices; $SD = 3.41$ hours, range: 1-16 hours). Further, 68% of the participants indicated that their daily routine during the sampling period was typical ("as usual"), 18% stated their daily routine was untypical ("I did things I usually don't do"), and 14% could not decide whether their daily routine was typical or untypical. In total, 60% of the participants reported that the study had no influence on their smartphone usage behavior. Of the 40% who indicated an influence, 7% stated that they used their smartphone more often, 2% said they were more aware of their usage behavior. 16% looked more often on the phone, 7% took the phone more often with them, and only 1% stated that the study had some influence on their actual smartphone usage behavior (7% provided no information on the nature of the specific influence).

Table 1

Descriptive statistics of questionnaire results.

	M	SD	Range
AQ	16.27	5.93	28.00
EQ	40.68	10.99	60.00
BAP	2.74	0.57	3.08
SPS	15.27	12.63	67.00
SIAS	23.18	14.01	72.00
Verbal IQ	106.97	10.26	54.00
BFSI: O	-0.07	0.71	4.20
BFSI: C	-0.13	0.69	4.07
BFSI: E	-0.15	0.68	3.89
BFSI: A	-0.04	0.72	3.97
BFSI: N	-0.07	0.79	4.61

Note. AQ, Autism-Spectrum Quotient; EQ, Empathy Quotient; BAP, Broader Autism Phenotype; SPS, Social Phobia Scale; SIAS, Social Interaction Anxiety Scale; Verbal IQ refers to the MWT-B, a German multiple choice vocabulary test; BFSI, Big Five Structure Inventory; O, openness to experience; C, conscientiousness; E, extraversion; A, agreeableness; N, emotional stability/absence of neuroticism; note that BFSI values reflect person parameters of the PCM (rather than sum scores; Masters, 1982).

Experience Sampling

The ESM survey analysis is based on a sample of 220 participants. Descriptive statistics of the questionnaire results of this subsample can be found in the Supplemental Material.

Confirmatory Analyses. We replicated the finding by Bryant et al. (2013) that participants think more about actions (M_{action} = 0.56, SD_{action} = 0.18) than about mental states (M_{mental} = 0.28, SD_{mental} = 0.18) in their everyday life, $t(219) = -12.92$, $p < .001$, g = -0.87, $CI_{95\%}$ = [-1.07, -0.67].

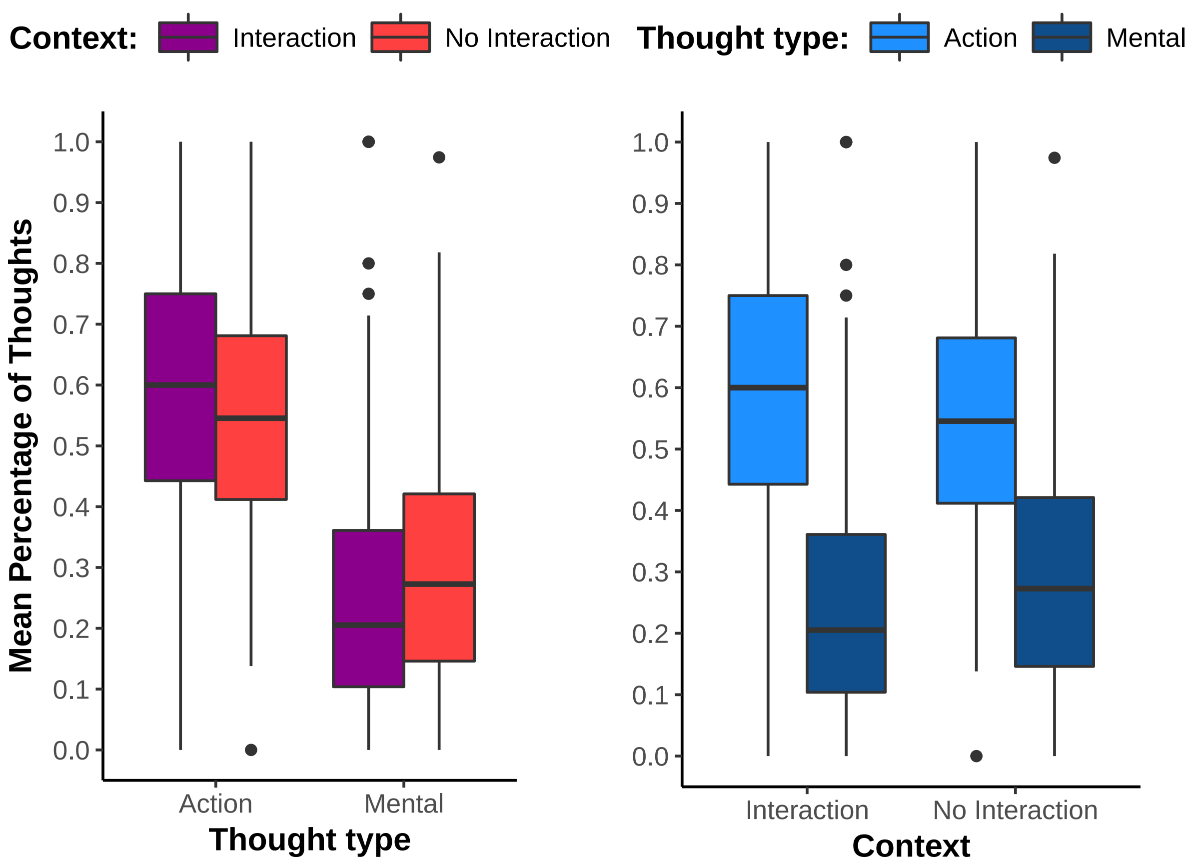

Figure 1. Mean frequency of thought type. This figure illustrates the mean frequency of thoughts about actions and mental states in percent.

Further, we investigated whether the frequency of thoughts about mental states and actions was context-dependent. To this end, we calculated thought types (mental state, action, miscalleneous) relative to the context in which they occurred (interaction and alone) and performed a 2 × 2 repeated measures analysis of variance (ANOVA) with the within-participants factors thought type (mental state vs. action) and context (interaction vs. alone). See Figure 1 for boxplots. Mirroring the finding of the t test reported above, we found a significant main effect of thought type, $F(1, 219) = 171.57$, $MSE = 0.11$, $p < .001$, $\hat{\eta}^2_G = .349$. Due to the way frequency scores were calculated for this analysis (thought type relative to context), no main effect of context was observed, $F(1, 219) = 1.41$, $MSE = 0.00$, $p = .236$, $\hat{\eta}^2_G = .000$. Crucially, we found a significant interaction between thought type and context, $F(1, 219) = 14.90$, $MSE = 0.03$, $p < .001$, $\hat{\eta}^2_G = .011$. Bonferroni-corrected post-hoc t tests showed significant differences between all conditions. Action thoughts occured more frequently when the participants were interacting (M = 0.59, SD = 0.22) than when they were alone (M = 0.54, SD = 0.19), $t(219) = 3.75$, $p = .001$, g = 0.25, $CI_{95\%}$ = [0.06, 0.44]. Conversely, mental state thoughts occured more often when the participants were alone (M = 0.29, SD = 0.19) than when they were interacting (M = 0.26, SD = 0.20), $t(219) = -3.39$, $p = .005$, g = -0.23, $CI_{95\%}$ = [-0.42, -0.04]. Further, the post-hoc t tests showed that people more frequently thought about actions than mental states when they were interacting $t(219) = -12.87$, $p < .001$, g = -0.87, $CI_{95\%}$ = [-1.06, -0.67]. In parallel, when alone, participants also thought more frequently about actions than about mental states $t(219) = -10.58$, $p < .001$, g = -0.71, $CI_{95\%}$ = [-0.91, -0.52].

Additionally, we addressed the question whether the participants' mental state thoughts referred more frequently to the past, present, or future in a one-way repeated measures ANOVA with the within-factor timeline (past, present, future). The respective boxplots are shown in Figure 2a. This analysis revealed a significant difference between the times to which the participants' thoughts referred, $F(1.65, 360.54) = 241.10$, $MSE = 0.07$, $p < .001$, $\hat{\eta}^2_G = .507$. Bonferroni-corrected post-hoc t tests showed that the participants' mental state thoughts referred more frequently to the present (M = 0.59, SD = 0.25) than to the past(M = 0.12, SD = 0.15), $t(219) = -20.32$, $p = .030$, g = -1.37, $CI_{95\%}$ = [-1.58,

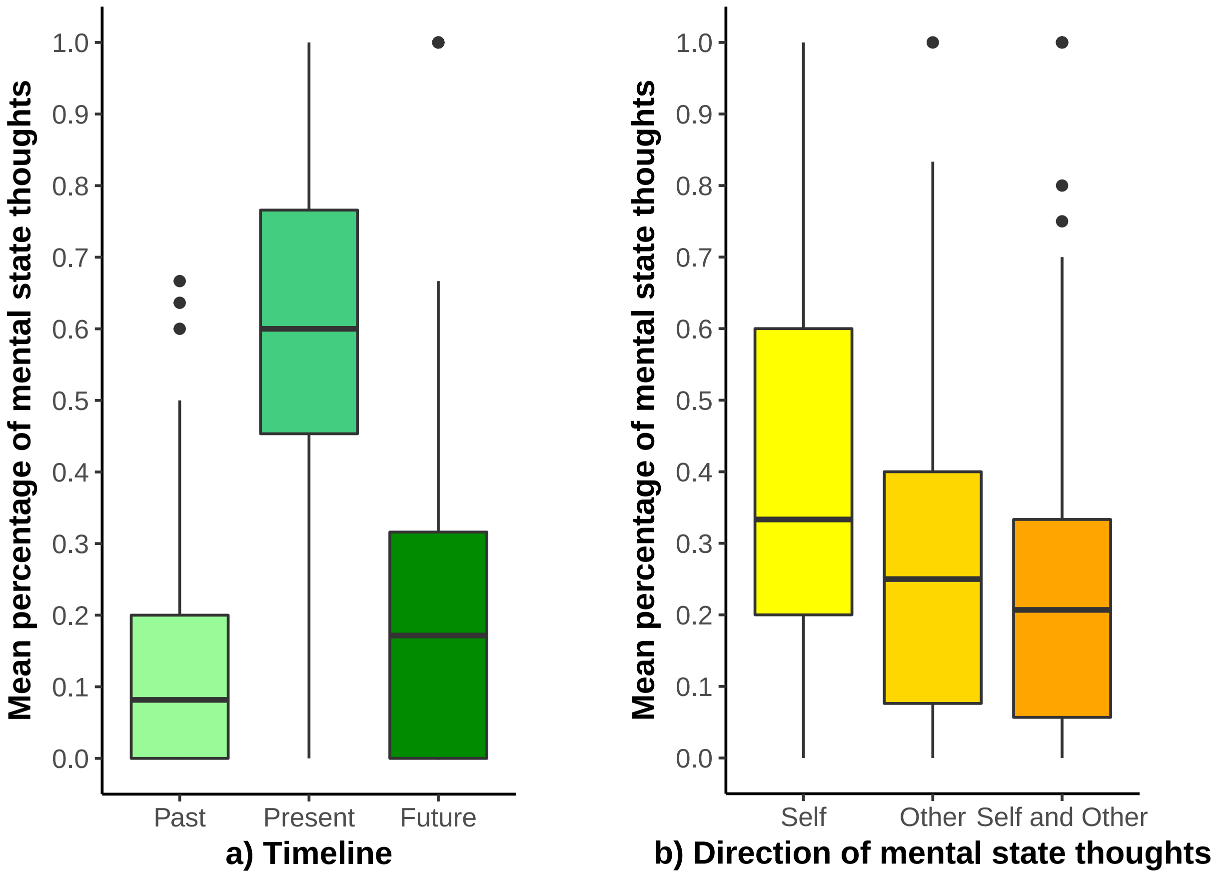

Figure 2. a) Mean percentage of the timeline of the thought. b) Mean percentage of the direction of mental state thoughts.

-1.16] and the future (M = 0.20, SD = 0.20), $t(219) = 14.45$, $p < .001$, $g = 0.97$, $CI_{95\%}$ = [0.77, 1.17]. Further, their mental state thoughts more often referred to the future than to the the past $t(219) = 14.45$, $p < .001$, $g = 0.97$, $CI_{95\%}$ = [0.77, 1.17].

We also analyzed whether the participants' mental state thoughts more frequently referred to themselves, others, or themeselves and others. Boxplots can be found in Figure 2b. A one-way repeated measures ANOVA with the factor direction (self, other, self and other) yielded a significant difference between the directions of mental state thoughts, $F(1.9, 416.76) = 22.46$, $MSE = 0.08$, $p < .001$, $\hat{\eta}^2_G = .088$. Bonferroni corrected post-hoc t tests indicated that mental state thoughts referred more frequently to oneself (M = 0.40, SD = 0.27) than to others (M = 0.26, SD = 0.22), $t(219) = 4.76$, $p < .001$, $g = 0.32$, $CI_{95\%}$ =

[0.13, 0.51], and to oneself and others ($M = 0.23$, $SD = 0.21$), $t(219) = 6.14$, $p < .001$, $g = 0.41$, $CI_{95\%} = [0.22, 0.6]$. There was no difference in the frequency of mental state thoughts referring to others versus oneself and others, $t(219) = 1.32$, $p = .566$, $g = 0.09$, $CI_{95\%} = [-0.1, 0.28]$.

Finally, we asked whether our data would indicate an association of the level of autistic traits with the reported amount of mental state thoughts. The corresponding partial correlation was controlled for verbal IQ (MWT-B), social phobia (SPS), social anxiety (SIAS), and Big Five personality dimensions (BFSI). We found no significant relation between the level of autistic traits and the amount of mental state thoughts in this analysis, $r = 0.02$, $p = > .999$, 95%CI = [-0.12, 0.15], ($p_{\text{uncorrected}} = .786$).

To analyze the relationship between autistic traits and the emotional valence while cognitively engaging with the social world, we computed the mean valence of all thoughts that were (1) categorized as mental state or action and (2) that were directed to others (i.e. the categories "other" and "self and other"). The logged valence was coded as -1 (negative), 0 (neutral), or 1 (positive). The partial correlation between the level of autistic traits and the valence of thoughts that addressed the social world ($M = 0.21$, $SD = 0.28$; controlling for the same variables as above) revealed no significant relationship between these two variables, $r = 0.01$, $p = > .999$, 95%CI = [-0.12, 0.14], ($p_{\text{uncorrected}} = .884$).

Exploratory Analysis. It was previously described that people with autism use more conscious and explicit routes to reason about other's mental states in contrast to the comparably effortless mentalizing of people without autism (Hill & Frith, 2003). This leads to the assumption that especially during social interaction, a situation which is challenging for many people with autism, they should be explicitly reasoning about mental states (cf., Begeer et al., 2010). Thus, people with autism might be more aware of their mental state reasoning and might use such an explicit form of mentalizing more frequently than people without autism. With our data, we can indirectly test this assumption by investigating whether higher autistic traits are associated with an increased frequency of mental state

Table 2

Descriptive statistics of smartphone usage behavior

	M	SD	Range
Total number of communication events	1981	1470	8609
Total duration of communication events (in h)	24.08	17.16	94.72
Total number of social media events	641	770	5276
Total duration of social media events (in h)	14.7	14.18	71.23
Number of contacts	189	138	1039

Note. The total number of events and the total sum of event durations in the 30-day-long logging period is shown. The number of contacts was recorded at the end of the sampling period.

thoughts when our participants were interacting with others. However, we found no evidence for such a relationship in a partial correlation between the level of autistic traits and the amount of mental state thoughts during social interaction, while controlling for the influence of verbal IQ (MWT-B), social phobia (SPS), social anxiety (SIAS), and Big Five personality dimensions (BFSI), r = -0.01, p = .937, 95%CI [-0.14, 0.13]. Note that the p value of this exploratory analysis is uncorrected and should not be interpreted.

Social Interaction via Smartphone

The analysis of social interaction via smartphone is based on a subsample of 223 participants. Descriptive statistics of the questionnaire results of this subsample are provided in the Supplemental Material. Table 2 gives an overview of the descriptive statistics of the logged smartphone usage behavior that served as measures of interest. On average, the participants used communication apps for 24 hours in the 30-day-long logging period (SD = 17 hours). This corresponds to a mean of 48 minutes a day (SD = 34 minutes). Social media apps were used for 15 hours on average in the sampling period (SD = 14 hours). This equals a mean social media duration of 29 minutes a day (*SD* = 28 minutes). On average, our participants had 189 contacts saved on their smartphone (*SD* = 138 contacts). These app usage rates reflect the previously reported so-called *application micro-usage* behavior (Ferreira, Goncalves, Kostakos, Barkhuus, & Dey, 2014). Our participants spent on average 48 seconds using an app from the *communication* category (*SD* = 26 seconds). The average usage duration of apps from the *social media* category was 91 seconds (*SD* = 74 seconds).

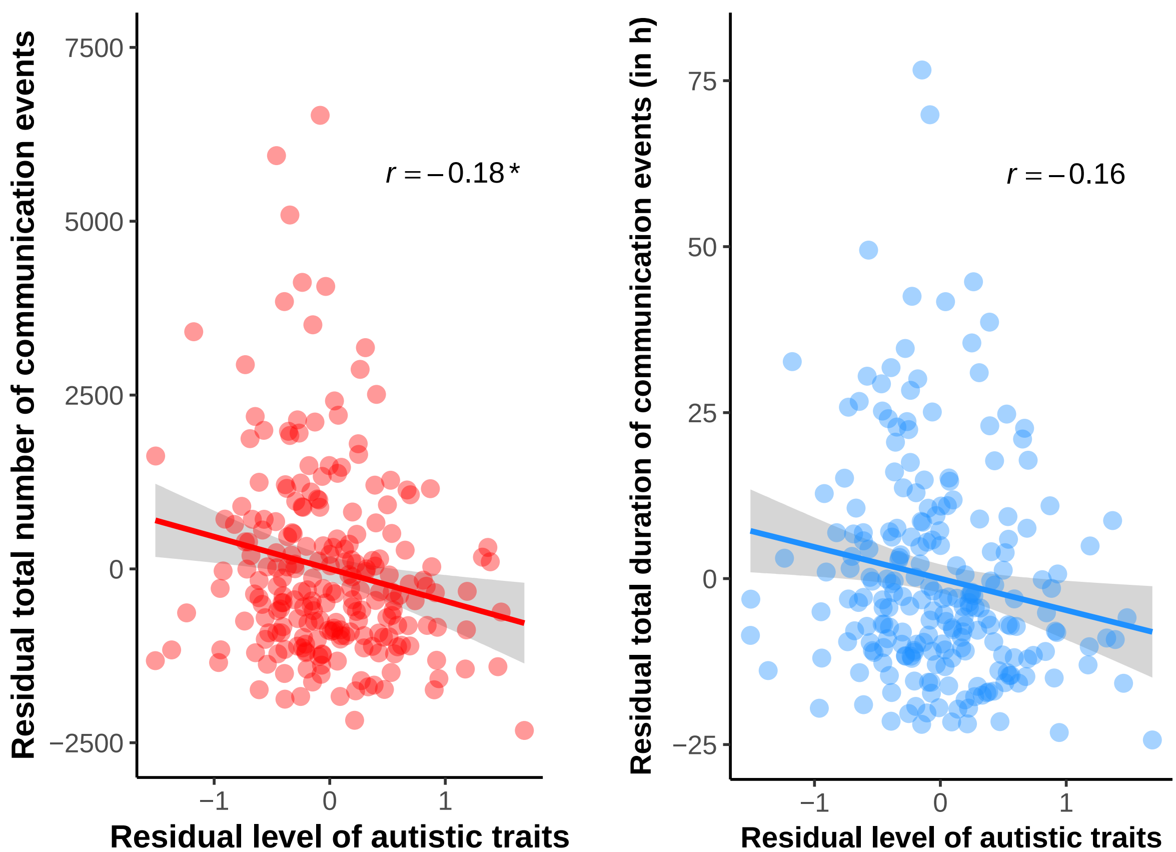

Figure 3. Scatterplots showing the relationship between level of autistic traits and communication via smartphone. Correlation coefficients are from the partial correlation of the masures of interest, controlled for verbal IQ (MWT-B), social phobia (SPS), social anxiety (SIAS), and Big Five personality dimensions (BFSI). Note: $p < .05^*$ after correcting for multiple comparisons.

Confirmatory Analyses. All partial correlations were again controlled for verbal IQ (MWT-B), social phobia (SPS), social anxiety (SIAS), and Big Five personality dimensions (BFSI). Scatterplots displaying the relationship between the level of autistic traits and the the amount of communication via smartphone can be found in Figure 3. A main aim of our study was to test whether the participants' level of autistic traits was associated with their amount of communication via smartphone. After correcting for multiple comparisons, we found a significant negative correlation between level of autistic traits and the total number of communication events, r = -0.18, p = .048, 95%CI = [-0.31, -0.05], ($p_{\text{uncorrected}}$ = .007). The negative correlation between the level of autistic traits and the total duration of communication events was not significant after the Holm-Bonferroni adjustment, r = -0.16, p = .111, 95%CI = [-0.29, -0.03], ($p_{\text{uncorrected}}$ = .019).

We found no significant correlation between the level of autistic traits and exposure to the social world, operationalized via the total number of social media events, r = -0.04, p = > .999, 95%CI = [-0.18, 0.09], ($p_{\text{uncorrected}}$ = .516). Also the correlation between the level of autistic traits and the total duration of social media events was not significant, r = -0.05, p = > .999, 95%CI = [-0.18, 0.09], ($p_{\text{uncorrected}}$ = .483).

There was also no significant correlation between the level of autistic traits and the number of contacts saved on the participants' smartphone, r = -0.04, p = > .999, 95%CI = [-0.17, 0.10], ($p_{\text{uncorrected}}$ = .583).

Exploratory Analyses. We ran a regression analysis to further explore the significant correlation between the level of autistic traits and the number of communication events. We were interested in the specific influence of the level of autistic traits on communication via smartphone. Previous literature suggested that social anxiety, social phobia, and autistic traits are strongly related, but still distinct phenomena (Kleberg et al., 2017; Liew et al., 2015), To better assess the differential contributions of each domain, we introduced social anxiety, as well as the interaction between social anxiety and autistic traits as additional predictors into the model. The dimension extraversion from the Big Five personality inventory was added as a control variable.

For the confirmatory analyses, we used the level of autistic traits, a compound score of the participants' AQ, EQ, and BAP scores. However, a reliability analysis of these three z-transformed scores revealed that EQ scores were not a good predictor of AQ and BAP scores, implying that the EQ measured a different construct than the AQ and BAP. With the EQ included, Cronbach's α was 0.78. When the EQ was left out, Cronbach's α increased to 0.86. Further, also the EQ's discriminatory power was the lowest of the three measures ($r_{\text{EQ}} = 0.46$, $r_{\text{AQ}} = 0.69$, $r_{\text{BAP}} = 0.71$). Based on these results, we excluded the EQ from the following analysis and built a compound score only from z-transformed AQ and BAP scores to get a better estimate of the level of autistic traits.

A reliability analysis of the employed measures for social anxiety and social phobia (SPS and SIAS) revealed a Cronbach's α of 0.87 and a sufficient discriminatory power, $r =$ 0.77. This fits well with the conceptualization of the SIAS and SPS as complementary measures of the same underlying construct (Mattick & Clarke, 1998). Thus, for the following analyses, both measures were combined into one score for social anxiety.

The distributions of the independent variables indicated that a negative binomial regression model is appropriate. Figure 4 illustrates the model and provides the percent ratio of the Incident Rate Ratio [-100 * (1-$Exp(b)$]. The level of autistic traits significantly predicted the total number of communication events, $b =$ -0.21, $SE =$ 0.07, $Z =$ -2.88, $p =$ .004. Holding the other predictors constant, an increase of the level of autistic traits by one unit was associated with a decrease by 19% of communication via smartphone, operationalized via the total number of communication events. In contrast, social anxiety showed a significant positive relation to the total number of communication events, $b =$ 0.27, $SE =$ 0.07, $Z =$ 3.71, $p = <$ .001. Keeping all other predictors constant, a one unit increase of social anxiety was associated with a 31% increase of communication via smartphone. The interaction between the level of autistic traits and social anxiety did not significantly predict the communication via smartphone, $b =$ -0.01, $SE =$ 0.05, $Z =$ -0.24, $p =$ .807. Analoguous to social anxiety, the control variable extraversion was significantly positively related to the communication via smartphone, $b =$ 0.22, $SE =$ 0.08, $Z =$ 2.64, $p =$ .008. An increase of

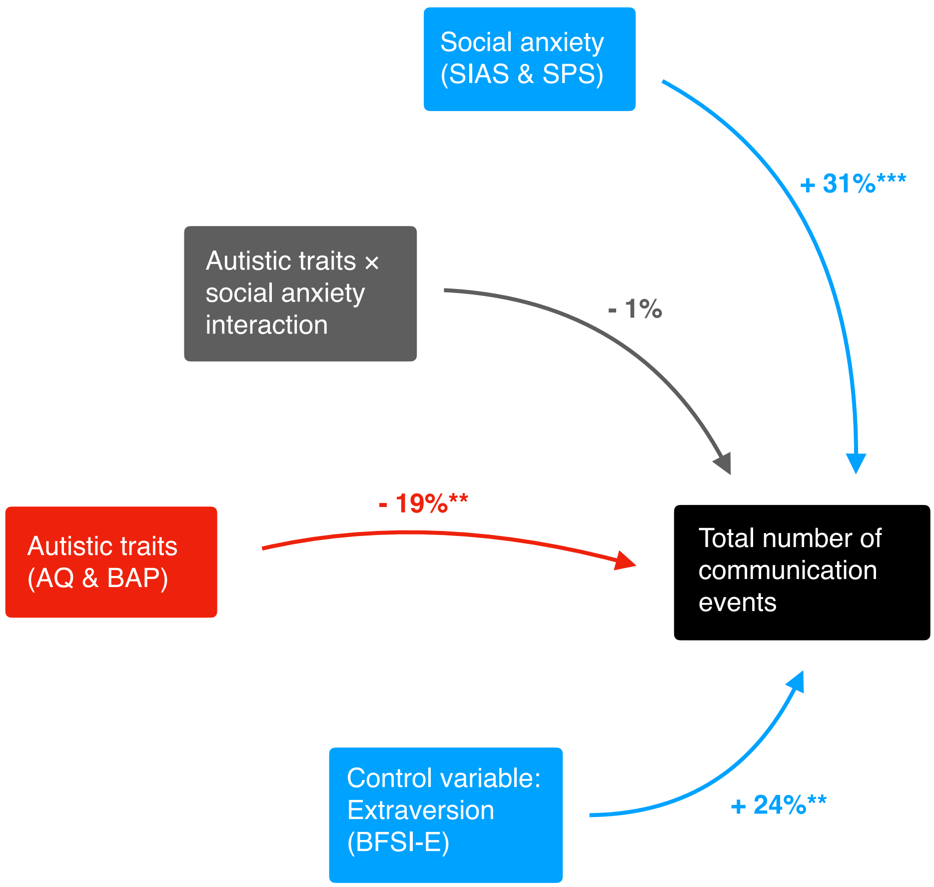

Figure 4. Schematic illustration of the exploratory negative binomial regression of smartphone usage data. The values show the the percent ratio of the Incident Rate Ratio [-100 * (1-$Exp(b)$]. Positive values indicitate a positive, negative values a negative predictive relationship between the independent variables and the total number of communication events ($p < .001$***, $p < .01$**). Note that the p values of this exploratory analysis are not corrected for multiple comparisons and the predictive relations should not be generalized without further cross-validation.

extraversion by one unit lead to a 24 % increase of the communication via smartphone, keeping the other predictors constant. It is important to note that due to the exploratory nature of this analysis, the found associations should not be readily generalized without further cross-validation in a new sample.

Discussion

We investigated the nature of mentalizing, and the links between autistic traits, mentalizing, and social interaction in everyday life. Corresponding to Bryant et al.'s (2013) findings, adults thought twice as much about actions than about mental states. Further, we found a similar context-specific variation. Our participants reported more thoughts about actions when they were interacting with others as compared to when they were alone and vice versa. Based on the idea that this form of mentalizing is effortful and resource-consuming and that our (neuro-)cognitive system works cost-efficiently (Bullmore & Sporns, 2012; Fiebich & Coltheart, 2015), we argue that overall, mental state thoughts occur less frequently than action thoughts because processing of mental states is cognitively costly. Rather, they occur preferably when we are alone, a situation in which cognitive resources are not occupied by the multitude of social information that has to be processed during interaction.

In our sample, mentalizing in everyday life was mainly used to process current mental states and only to a minor fraction dealt with past and future mental states. Further, paralleling Bryant et al. (2013), we found that most mental state thoughts were about one's own mental state. Yet, next to self- and other-directed thoughts, we introduced a third category to classify thoughts that referred to oneself and others because sometimes this cannot be disentangled. Our findings suggest that Bryant et al. underestimated the amount of thoughts that –at least partially– refer to others. Our results show that about half of the mental state thoughts in our sample were directed to others or others and oneself.

In contrast to what can be postulated based on previous literature (cf., Frith et al., 1994), autistic traits were not related to a reduced use of mentalizing. Moreover, our findings speak against the claim derived from the social motivation hypothesis (e.g., Chevallier et al.,

2012) that higher autistic traits entail a reduced intrinsic reward from engaging with the social world. We found no relationship between autistic traits and the valence of thoughts that addressed the social world.

As hypothesized, autistic traits were negatively correlated with communication via phone calls or text messages. The exploratory regression analysis points to additional details on the nature of this relationship. An increase of autistic traits was associated with a decrease in communication via smartphone. Interestingly, there was no interaction between autistic traits and social anxiety, and social anxiety had a reverse effect on the amount of communication. First, this adds to evidence that both phenomena are overlapping but yet distinct (Kleberg et al., 2017; Liew et al., 2015). Second, it allows for speculating that while for people with increased social anxiety communication via smartphone could serve a compensatory purpose, this may not be the case for people with elevated autistic traits (cf., van Schalkwyk et al., 2017). Further research is necessary to follow up on this result.

Autistic traits were not associated with the amount of social media usage, a more indirect way of getting in touch with the social world. We also found no relation between autistic traits and social network size (Kreider et al., 2016). This does not support the notion that high autistic traits are associated with a reduced interest in the social world (Chevallier et al., 2012). Further, this suggests an interesting dissociation between different ways of engaging with the social world. The reduced communication could be related to difficulties with fast and flexible social information processing, required for reciprocal social interactions. Unlike communication via smartphone, social media usage can be entirely passive and follows clear rules (e.g., liking, retweeting, . . .). Thus, it may be less challenging for people with difficulties in reciprocal interaction (cf., van Schalkwyk et al., 2017).

Two methodological factors should be considered in the evaluation of our findings. First, compared to experimentally testing cognition in the lab, experience sampling introduces a considerable measurement error. For example, the thought categorization inevitably left room for ambiguity. Second, interaction via smartphone constitutes only a part of our social life. Our conclusions cannot be directly expanded to other forms of interaction. However, from an experimental psychologist's point of view, given the difficulty to study cognition and behavior outside the lab, even with these limitations both measures can be considered being relatively valid means to capture these phenomena.

Further, it is important to point out that the conclusions based on the examination of autistic traits in the general population cannot be readily generalized to autism. For example, previous work suggests that the AQ taps the same latent traits in people with and without autism, but that the same test scores do not necessarily reflect the same level of autistic traits (Murray, Booth, McKenzie, Kuenssberg, & O'Donnell, 2014). A next step would be to run the current study in a sample of people with an autism diagnosis. Such a study would deepen our understanding of the role computer-mediated social interaction plays in autism.

Our data provide evidence that thinking about other's and our own actions and mental states makes up most of our conscious cognitive processing. We show that elevated autistic traits are associated with reduced computer-mediated communication, potentially because reciprocal direct interaction is difficult for people with high autistic traits. Yet, autistic traits were unrelated to the general tendency to get in touch with the social world and with the social network size, indirectly supporting findings that people with autism seek social participation via technology (Mazurek, 2013).

Author Contributions

T. Schuwerk developed the study concept. T. Schuwerk, A. Hoesl and C. Stachl contributed to the study design. Data collection was performed by T. Schuwerk, L. Kaltefleiter, and C. Stachl. Data preprocessing and analysis was performed by T. Schuwerk, L. Kaltefleiter, Quay Au, and C. Stachl. T. Schuwerk and C. Stachl interpreted the results. T. Schuwerk, L. Kaltefleiter, and C. Stachl drafted the manuscript. All authors provided critical revisions and approved the final version of the manuscript for submission.

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