# How User Condition Affects Community Dynamics in a Forum on Autism

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**Abstract**

Individuals on the autistic spectrum and their families look for peer support in specialized online forums. These venues also attract advocates and people interested in autism, providing valuable first-hand experience. Previous research focused on quantifying how autistic individuals interact in online communities, and if they benefit from computer-mediated communication. However, there is limited quantitative understanding of the different roles that diagnosed individuals, family members, and neurotypical users play in these communities. This paper analyses Wrong Planet, a large online autism forum where users may openly state their condition in their profile. The sentiment, discourse, and network characteristics of content users contribute (and respond to) differs by user condition. Also, interaction patterns between users with different conditions shed light on the dynamics of the forum community. Content exchanges between family members and neurotypical users are emotionally charged and supportive; however, this support is less present in exchanges with diagnosed members. This paper gives insights on what factors facilitate participation of diagnosed users.

## 1 Introduction

In recent years media have increased public awareness of autism. At the same time, research in human-computer interaction has yielded better understanding of behaviours associated with autism, and of how information technology may assist individuals in the autistic spectrum. Online health communities help deliver information and social support to such individuals and to their families (De Choudhury and De 2014), and foster the creation of advocacy groups involving both affected and unaffected participants (Davies 2015). Computer-mediated communication helps individuals with autism engage in rewarding interactions by mitigating difficulties they may experience with aspects of face-to-face communication, such as timely processing of nonverbal cues, or lack of control over the interaction environment (Jordan 2010).

While recent studies characterize the content of autism communities as a whole (see e.g. Saha and Agarwal 2016), there is limited knowledge on the differences, if any, in how affected individuals, family members, users doubting their condition, and neurotypical users participate. We address the issue analysing the forum section of Wrong Planet,

> [. . . ] the web community designed for individuals (and parents / professionals of those) with Autism, Asperger's Syndrome, ADHD, PDDs, and other neurological differences. [1]

Users in Wrong Planet can opt-int to disclose their diagnosis (or lack of thereof) in their public profile; this ground truth forms the basis of our analysis throughout the paper, which is organized as follows. We begin with an overview of related literature, the forum data used, and the methods of analysis. The next section tackles our first research question:

> **Q1** Do users in different conditions post different content?

Quantitative and sentiment analyses of profiles, posts, and quotes yield a characterization of users in different roles, enriched by analysing for any posted content the surrounding discussion. The next two sections respectively study if users in different roles respond coherently with the sentiment of the discussion, and if the role of a post's author affects the sentiment of the responses to the post. These tasks provide answers to the second research question:

> **Q2** Do users in different conditions react differently to content?

Then, we consider whom users in different roles interact with by analysing quoting patterns between users. This clarifies the direction and reciprocity of content exchange, and addresses the third research question:

> **Q3** Do users in different conditions interact differently with users in other conditions?

The following section builds upon the observed differences in how different roles contribute, react, and interact, and investigates which factors correlate with participation in a discussion:

> **Q4** Do users in different conditions contribute differently to a discussion based on its sentiment and participants?

Finally, the last sections provide a working proof that user roles can be quantitatively discerned though automated classification, and discuss the implications of the study.

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[1] http://wrongplanet.net/, accessed on 4/1/2017

# 2 Related Work

## 2.1 Autism Spectrum Disorder

Autism spectrum disorders refer to a range of mental and behavioural conditions, including autism and Aspergers syndrome. These conditions are associated with difficulties in social interaction and communication, and restricted, repetitive interests and behaviours (World Health Organization 1992). However, individuals may exhibit impairments in only some of these areas, and to varying extent. At the same time, other conditions, such as mood and anxiety disorders, are frequent comorbidities (Ekblad 2013). Individuals on the spectrum may experience difficulties in timely processing of figurative language and nonverbal cues, identifying and expressing emotion, and taking someone else's perspective (Lockwood et al. 2013). Also, individuals may show hypersensitivity to environmental factors (Jordan 2010), and interest in a limited number idiosyncratic topics (Caldwell-Harris and Jordan 2014; Rouhizadeh et al. 2014). These impairments often make it difficult to engage in satisfying interaction. This paper investigates novel ways to measure manifestations of such impairments in the online context.

## 2.2 Autism Diagnosis

One in 68 children in the US has been identified with autism spectrum disorder.[2] Research is still ongoing to uncover the biological and environmental causes; while genetics currently explain only a fraction of autism cases, it is estimated that between 20% and 50% of family members fall into at least one broader autism phenotype – sub-clinical yet qualitatively similar forms of autism symptoms (Sasson et al. 2013). While only professionals can diagnose autism spectrum disorders (American Psychiatric Association 2013), several self-test resources are available online, spreading awareness on the condition (Ekblad 2013). This paper compares online behavior of users with clinical diagnosis and self-assessed diagnosis, family members, users suspecting their condition, and neurotypical users.

## 2.3 Autism Online

The Web is an enabling technology for the socialization of individuals with autism (Mazurek 2013). Computer-mediated communication may lessen anxiety felt during face-to-face interaction, as it does not require real-time processing of conversational partners' emotions and intentions, and can be carried on from familiar, controllable settings (Jordan 2010). Anonymity and privacy foster self-disclosure and self-advocacy of individuals with the condition and their families. In turn, personal blogs and online communities provide a wealth of first-hand knowledge to people suspecting their condition, to professionals, and to other users (De Choudhury and De 2014). We investigate how interaction between users in these different roles affects their participation online.

[2]Centers for Disease Control and Prevention, https://www.cdc.gov/ncbddd/autism/data.html, accessed on 5/1/2017

## 2.4 Autism Community Analysis

The increasing volume of public data allows large-scale, unobtrusive research of online autism communities and their users. A network analysis of mentions and replies to Twitter handles of popular autism bloggers shows unusually strong reciprocation (Saha and Agarwal 2016). Topics discussed in autism communities include well-being, mental health, and religion as a coping strategy, as well as relationship, education, and daily tasks that may prove challenging for autistic individuals (Ji et al. 2014). Results are mixed on whether bloggers on the spectrum write differently than neurotypical bloggers, in terms of sentiment and psycholinguistic categories (Newton, Kramer, and McIntosh 2009; Nguyen et al. 2015). However, measures based on these categories find differences in microblogs by autistic users, family members, and advocacy groups (Saha and Agarwal 2016). This paper adds an informative datapoint to previous research by analysing a large online forum with a rich, self-annotated ground truth on the role of its users – yielding a large sample size, low sampling bias, and a comprehensive outlook on user roles in one shared discussion venue.

# 3 Data

This section introduces the community focus of this study, describes the data we obtained, and details the limitations and ethical concerns associated with them.

## 3.1 Wrong Planet

Wrong Planet is a web community for people with autism-spectrum disorders, their families, and professionals. The centre of the community is the forum, where users discuss autism and related conditions, exchange experience and coping strategies, and engage in informal talk. Besides the forum, the community features articles and how-to guides, and maintains a youtube channel. Wrong Planet users have been the object of previous research (Davies 2015; Ekblad 2013; Caldwell-Harris and Jordan 2014; Jordan 2010), but this is the first study that analyses the entire forum.

## 3.2 Dataset

We crawled thread, post, and user profile information through a python script, excluding resources external to the site. Since we analyse only the plain text and metadata of posts, we encode links and images with their source, or alternative text when available. Also, as the forum's quoting template does not include links to the original posts, we use a heuristic algorithm to reconnect quoting and quoted posts. [3] The data gathered span dates 6/2004 – 10/2016. Table 1

[3]We strictly match the name of the quoted user (when available) with that of candidate quoted posts in the thread, and select as quoted post the one closest to the quoting post that approximately contains the quoted content (there exists a sublist of contents in the quoted post where all strings at matching indices have a partial-ratio string match of at least 80%, and all nested quotes strictly match). Note that quoting users may choose to cut or edit the quoted content, which makes heuristic matching necessary. We use the `fuzzywuzzy` python module for fuzzy string matching: https://github.com/seatgeek/fuzzywuzzy

| condition | users | posts | threads |
|---|---|---|---|
| Aspergers - Diagnosed | 2254 | 736525 | 138129 |
| Aspergers - Undiagnosed | 339 | 61546 | 24930 |
| Other ASD | 298 | 148799 | 32322 |
| Not sure if I have it or not | 311 | 46539 | 19595 |
| Family member | 107 | 5543 | 3062 |
| Neurotypical | 107 | 3191 | 1518 |
| showing diagnosis | 3416 | 1002141 | 156154 |
| overall | 48712 | 6115377 | 261857 |

Table 1: Cardinality of Wrong Planet dataset, global, and by diagnosis for those users making it public in their profiles.

shows the size of the dataset. Out of 48000 user profiles, 3400 make the diagnosis public. The rest of the paper will use the term "condition" to refer to the self-reported value for the "diagnosis" field in the user profile. For the sake of brevity, the rest of this paper will also use the following contractions for user conditions:

- AD: *Have Aspergers - Diagnosed*
- AU: *Aspergers - Undiagnosed*
- OA: *Other autism spectrum disorder*
- NS: *Not sure if I have it or not*
- FM: *Family member with Aspergers*
- NT: *Neurotypical*

Finally, the rest of the paper will refer to users that are certain of being on the spectrum (i.e. users in the AD, AU, or OA conditions) using term "neurodiverse"; work by Ekblad gives a more in-depth discussion on the concept of neurodiversity.

### 3.3 Limitations

All forum users, upon registration, are required to fill in the diagnosis field in their profile, with a pre-selected value of "Have Aspergers - Diagnosed". However, users need to opt-in to make their diagnosis public, which gives confidence in its accuracy. Nonetheless, there might be selection bias, as users choosing to show their diagnosis may be more open and/or sociable than the average forum participant.

### 3.4 Ethical Considerations

All data gathered are publicly accessible, without the need of registration to the site. All analyses were performed on aggregate data to preserve individual privacy. This work is based on self-reports of users in the forum, and does not make any diagnostic claims.

## 4 Measures

This paper uses several tools and measures of activity and content. This section describes each measure, and gives guidelines on how to interpret its value.

**Text complexity** To measure how difficult a text is to read, we use ARI, the Automated Readability Index (Smith and Senter 1967). ARI approximates the US grade level needed to understand a text: an ARI of 6 corresponds to a reader in Sixth Grade, etc.; thus, the higher the ARI, the *lower* the readability. ARI is a simple weighted sum on the number of characters per word and words per sentences in the text.

**Text sentiment** We gauge text sentiment using VADER (Hutto and Gilbert 2014), a lexicon- and rule-based tool specifically attuned to social media. VADER provides scores on the positive, negative, and neutral content of a text (non-negative and adding to 1), as well as a compound score for text polarity (from -1 to 1, negative to positive). In particular, we interpret the neutral score as an indicator of the (lack of) emotional charge in the text.

**Word categories** LIWC, the Linguistic Inquiry and Word Count program (Tausczik and Pennebaker 2010), is a lexicon-based tool that counts the number of words in a text that fall into different known categories, such as words relating to money or family. In this paper we use the lexicons for positive and negative emotions, sadness, anger, and anxiety. Note, however, that LIWC categories are relatively broad and subject to interpretation. We use both the raw counts and the fraction of words in a category.

**Text similarity** To measure how much two posts are similar, we use the cosine similarity of their (unigram) bag-of-words representations. This corresponds to the dot product of the normalized word histograms in the two texts: two identical texts have cosine similarity 1, two texts that do not share a single word 0.

**Text self-similarity** We also measure how repetitive text is, using its gzip compression ratio as an estimate of its entropy. We compute the compression ratio as the number of characters in the text, divided by the number of characters in it once compressed. The more repetitive the text is, the higher the compression ratio.

**Text topic** We extract the topics in the post corpus through LDA, Latent Dirichelet Allocation (Blei and Lafferty 2009). LDA defines a topic as probability distributions over the vocabulary, and posits that words in documents are drawn from a fixed number of topics. Given assumptions on their shape, LDA finds approximate values for the topic distributions in an unsupervised fashion. Finally, a trained LDA model can infer the most likely topic of a post, among the ones extracted.

Before proceeding to results, we remark that all differences, unless otherwise stated, are tested significant at $p < .01$ through ANOVA; additionally, differences between the six user conditions are also tested through Tukey HSD, that corrects for family-wise error rate in the case of multiple comparisons ($FWER < .05$ in all presented results).

# 5 Characterization

We start by analysing the typical contributions by users in different conditions. The next sections give quantitative characterizations of user profiles, posts, and quotes. This sheds light on the first research question:

**Q1** Do users in different conditions post different content?

## 5.1 User Profiles

User profiles in Wrong Planet contain both mandatory and optional items. Mandatory items, such as registration data, last access, and number of posts, describe the user's overall activity, and reveal changes in the composition of the forum over time. Optional items tell how much users disclose about themselves, a feature that previous research associated with sociability, with privacy concerns (Schrammel, Köffel, and Tscheligi 2009), and with perceived stigma and sense of belonging imparted by a diagnosis (De Choudhury and De 2014).

AD users have a larger activity timespan than AU, NS, and NT. AD entered the forum earlier than AU and NS, and OA earlier than NS. FM last browsed the forum less recently than neurodiverse, and NS (ANOVA $F$ respectively $8.5, 8.7, 5.7$). However, no differences in the number of posts and posts per day are significant (ANOVA $p > .05$). Since the resulting differences involve only few pairs of conditions, we conclude that the forum has seen similar presence and contribution by user condition over time. This also gives confidence that skews in data do not affect our analyses.

We group optional profile items into biographical information (age, gender, location, occupation, diagnosis), contact information (e.g. AIM, website, . . . ), and personalization (interests, signature, custom avatar, custom user phrase and status image). **Neurodiverse users disclose significantly more items than NS, NT and FM users overall** ($F = 20.3$), with NS disclosing more than NT. This difference is best explained by the number of personalization items disclosed (neurodiverse $>$ NS $>$ FM, NT, $F = 32.3$), and only partly by that of biographical items (AD, AU $>$ NT, $F = 6.0$), with no significant difference found in contact disclosure. Figure 1 shows the average disclosed items by category and user condition.

Controlling for number of posts, and days on forum, ordinary least squares regression (OLS) identifies a positive correlation between overall self-disclosure and the combination of posts and days for NT users, while user condition alone is a significant predictor for neurodiverse and NS users ($p < .01$).

## 5.2 Posts

While user profiles show no difference in the total number of posts, how users write reveals many details about them. First, we look at how prone users are to start or respond to a discussion. This is tied to user roles in the discussion: initiators often request help or information, while respondents share support or knowledge. Then, we characterize how word and sentiment categories differ by user condition. On the one hand this sketches a common psycholinguistic portrait for users in each condition. On the other hand it sheds light on whether autistic traits (such as lack of expressed emotions, mood disorders, self-repetition) leave traces in online communication. Finally, we extract the topics of discussion in the community, and show differences in their distribution by user condition.

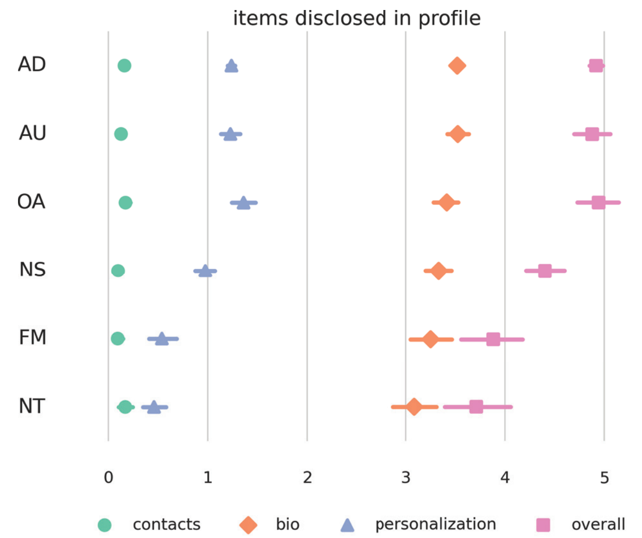


Figure 1: Number of optional items filled in user profile, by condition. Neurodiverse provide more details overall – mainly to personalize the profile, not to provide contacts.

**Posts and discussions** Data show no significant differences in the number discussion threads and posts per discussion by user condition (ANOVA $p > .05$). However, **neurodiverse users initiate a smaller fraction of the discussions they engage in** than NS, NT and FM, with NS initiating less threads than FM ($F = 16.4$). FM initiate more threads per post written than any other user group save NT ($F = 8.3$). This is somewhat surprising, since the site targets the needs of neurodiverse users.

**Sentiment, word categories, self-similarity** Figure 2 shows how user conditions differ by post content, through an analysis of post sentiment, fraction of words in categories associated with negative emotions (anger, sadness, anxiety), and self-similarity. **NT users write the most emotionally charged** (lower neutral scores) **and positively polarized posts** (positive compound scores). FM users, like NT users, post more positively polarized content than neurodiverse and NS users; however, compared to NT users, **FM show less emotionally charged content** (approximately as much as OA users and less than AD, AU, NS), **and use less words associated with negative emotions**. **NS individuals express the most words related to anxiety** (together with NT, and more than neurodiverse and FM users). Among neurodiverse users, **OA write the least charged posts across all dimensions**. Surprisingly, **neurodiverse users write the least repetitive posts**, both according to compression ratio (which would discount long repeated character streaks within each

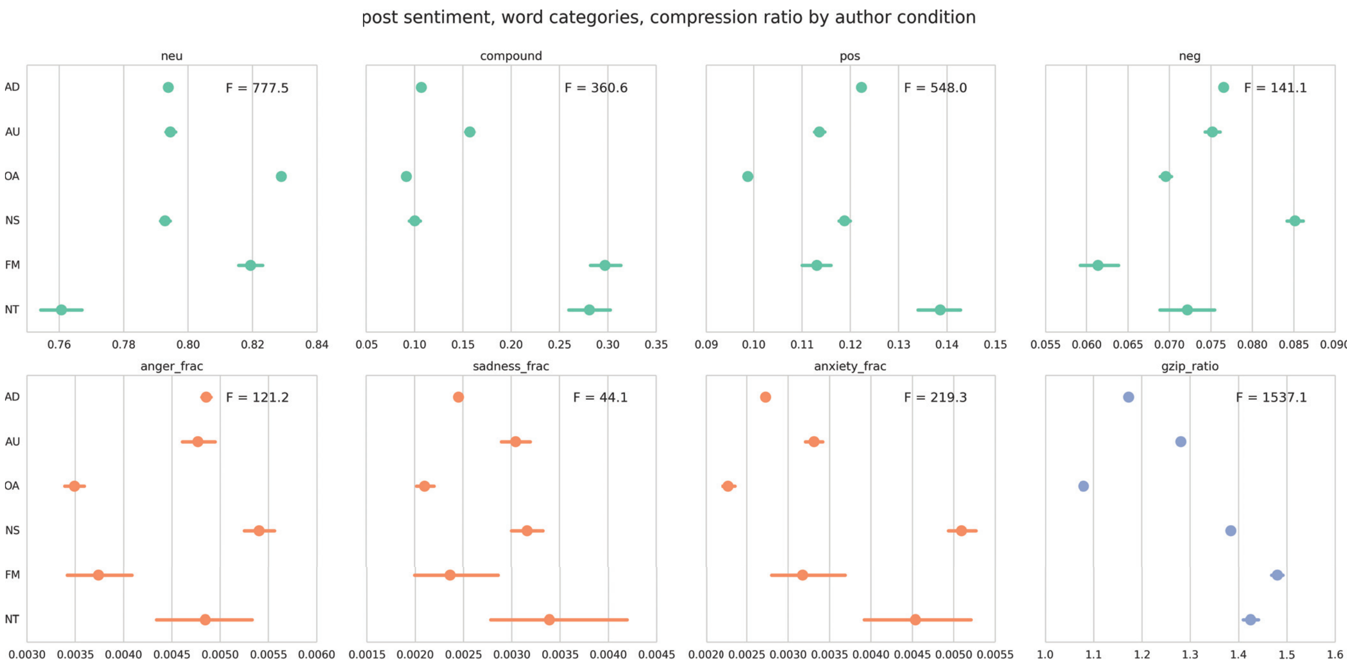


Figure 2: Sentiment (coloured in green), word categories (orange), and compression ratio (blue) for posts, by author condition.

post) and pairwise cosine similarity of their posts (which accounts for repetitions of similar words in different posts).

**Topics** We automatically extract ten topics using LDA, from the entire corpus – thus including posts by users not showing their diagnosis. We run four passes of LDA, to avoid possible influences of serial topic drift in the corpus. Table 2 shows the top ten words for the resulting topics; we manually summarized each topic into a one-word label. The topics seem internally coherent, and meaningful for the forum. We then compare topic proportion per post by user condition. NT and FM users show no statistical differences in the adoption of topics *web*, *visualization*, *relationship*, *nature*, and *daily*, and **neurodiverse users show collectively distinct values from NT and FM users** on topics *autism, cognitive, duties* (less than FM and NT), *daily, nature, relationship, visual, web* (more than FM and NT). There are statistical differences within the neurodiverse condition: FM show the highest proportion of autism, cognitive, duties topics; NT the highest proportion of *belief* and *cognitive*; OA *nature* and *visual*; AD topics *government* and *web*. Note that, interestingly, topic *autism* sees lower adoption by neurodiverse users.

## 5.3 Quotes

Quotes are high-precision devices for identifying point and counterpoint in online conversation, since quoting users choose to explicitly acknowledge the quoted post. We first investigate how and how much users in different conditions use quotes. Then, we show how the quoted content, and content posted in reply to quotes, differ by user condition.

**Quote quantity** **Posts by NT and FM users quote and are quoted more** than posts by neurodiverse and NS ($F = 214.0$ and $F = 262.9$). There is no significant difference in the number of quotes to users' own previous posts. **When users do quote, they differ in how**. AD and OA nest quotes: they quote previously quoted passages, thus hauling several steps of the conversation into each new message ($F = 213.0$). FM quote the most posts in each quoting post ($F = 28.39$), while NT users split single quoted posts into several smaller passages ($F = 44.2$). These different quoting modes suggest differences in how much users reciprocate quotes. For each user, we compute the total number of quotes to and from each other user, and take the difference (in absolute value). The mean of this number is the fraction of unmatched references with other users. Using this metric, FM users reciprocate significantly less than AD, AU, and NS users ($F = 2.9, p = .012$).

**Quote sentiment, word categories, complexity** FM users quote the most complex text according to ARI ($F = 14.3$), significantly more than neurodiverse and NS, and not differently from NT users. However, the complexity of the text FM and NT users reply with is not significantly different from that from AD and AU users: OA reply with the most complex, and NS with the simplest text ($F = 194.8$). FM users, in line with their own post production in the absence of quotes, quote ($F = 9.5$) and reply with ($F = 47.1$) the least emotionally charged content, and with the least percentage of words in negative emotion categories. NS users quote ($F = 33.1$) and reply with ($F = 72.1$) more anxiety words than neurodiverse users, confirming their main posting characteristic.

Summarizing, the answer to the first research question is that users in different conditions contribute significantly different content. In particular, users in different conditions

| topic | top words | F |
|---|---|---|
| *government* | vengeance government country law war right state american world rights | 2110.4 |
| *autism* | autism social autistic asperger diagnosed diagnosis aspie spectrum different nt | 1592.5 |
| *web* | http com youtube www watch jpg img welcome wp albums | 704.3 |
| *belief* | god way believe person post point mean things thread good | 205.3 |
| *cognitive* | feel things ve want way life going good said friends | 2608.5 |
| *visual* | iconlol iconbiggrin iconsmile love music good iconrazz iconeek oh iconwink | 586.5 |
| *daily* | day sleep night eat food morning ve going bed good | 81.5 |
| *nature* | world years life earth animals human space new live humans | 1502.8 |
| *duties* | work school job good need money new year got ve | 591.3 |
| *relationship* | women look men woman guy man guys girls girl nice | 188.8 |

Table 2: Topics, top words, and $F$ statistic for their proportion, by condition. Since LDA is unsupervised, topic names are manually assigned on the basis of the top words in each.

**quoting_emo ∼ qtd_diag*qtd_emo**

| y=quoting_emo[quoting_anxiety] | coeff | p |
|---|---|---|
| qtd_emo[T.anxiety] | 1.3767 | 0.006 |
| qtd_diag[T.NT]:qtd_emo[T.positive_affect] | 2.5763 | 0.006 |
| **y=quoting_emo[quoting_negative_affect]** | | |
| intercept | -1.4813 | 0.034 |
| **y=quoting_emo[quoting_positive_affect]** | | |
| intercept | 0.7906 | 0.029 |
| qtd_diag[T.AD] | -1.4483 | 0.000 |
| qtd_diag[T.NS] | -1.0041 | 0.010 |
| qtd_diag[T.OA] | -1.1048 | 0.003 |
| qtd_diag[T.NT]:qtd_emo[T.negative_affect] | 2.7291 | 0.037 |
| qtd_diag[T.AD]:qtd_emo[T.positive_affect] | 1.4568 | 0.001 |
| qtd_diag[T.NT]:qtd_emo[T.positive_affect] | 2.6710 | 0.004 |
| qtd_diag[T.NS]:qtd_emo[T.positive_affect] | 1.2306 | 0.013 |
| qtd_diag[T.OA]:qtd_emo[T.positive_affect] | 1.4960 | 0.002 |

Table 3: Quoted user's condition and prevailing sentiment in the quoted post as predictors of the prevailing sentiment in a reply, using multinomial logistic regression (FM is the reference condition). Only significant results are shown ($p < .05$). Model log-likelihood ratio $LLR = 2802$, $p < .001$, pseudo-$R^2 = .033$.

differ significantly in how much they disclose about themselves, in their propensity to initiate discussion, in the emotional and topical content of their posts, and in how and what they quote. While this section characterized user conditions by their own contributions, the next section investigates how users in different conditions differ in reacting to content "around" their contributions.

## 6 Reaction to Content

Individuals on the autistic spectrum often show difficulties in correctly identifying emotion and responding appropriately. Also, user responses are likely to be strongly influenced by each user's role in the forum (e.g. a NT user may be more likely respond to sad content with positive content, to provide emotional support). First, we investigate if the sentiment expressed in users' posts is coherent with that of the surrounding discussion. Then, we verify if the condition of a post's author influences the emotional content of replies to the post. This addresses the second research question:

**Q2** Do users in different conditions react differently to content?

### 6.1 Emotional Coherence

For each post, we compute its deviation from the discussion, taking the difference of the post's sentiment and fraction of words in emotional categories with the corresponding mean score for posts by other users in the discussion. **Neurodiverse users are more coherent with the thread's polarity** than FM, NT and NS users ($F = 1991.1$); NT and FM posts show a more positive polarity. Neurodiverse users also deviate more from the thread's sentiment on negative threads, although in no clear direction ($F = 155.4$). FM deviate the least from the thread's emotional charge, in contrast with AD and OA users ($F = 267.5$). AD and OA users also deviate the least from the thread's anxiety ($F = 217.0$).

### 6.2 Emotional Response

Users in different conditions receive replies with different emotional content. We extract the prevailing sentiment in the emotional word categories for each post (among positive and negative affect, anger, anxiety, sadness). In particular, we first compute the $z-$score of the number of words in each category across all posts, to account for categories that may be sparser or assume smaller values. Then, we label each post with the category with the highest $z-$score – i.e., the most extreme value relative to scores in other categories.

Quotes clearly identify post-and-reply pairs. We train a multinomial logistic regression model where quoted user condition and prevailing sentiment in the quoted post predict the prevailing sentiment in the quoting post. Results are reported in Table 3. When the main sentiment in the reply is anxiety, it happens in response to other anxiety, or positive emotions in NTs' posts. Intuitively, negative affect has negative bias in receiving quotes, positive affect positive bias. Surprisingly, **quoted posts authored by AD, NS, and OA users receive less positive responses, unless the main sentiment in their post was positive** to begin with. NT users, on the contrary, are reciprocated with positive affect when contributing either positive or negative posts.

## 7 Group Interaction

After characterizing user content in isolation, and how users content affects and is affected by the surrounding discussion, we analyse how users in different conditions interact with

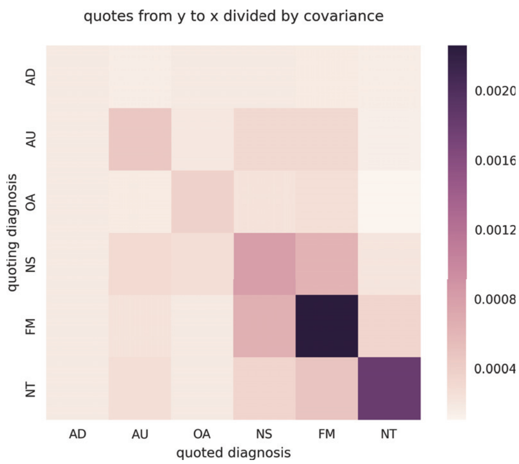


Figure 3: Number of quotes exchanged between users by condition (y axis: condition of the quoting user, x axis: condition of the quoted user). Data are normalized by the covariance of the matrix, to account for the overabundance of quotes from/to the AD condition.

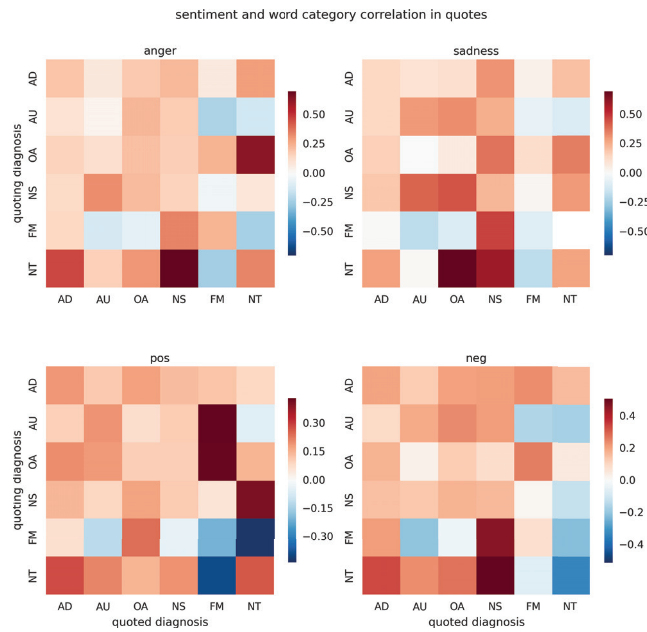


Figure 4: Correlations for selected sentiment and word categories between quoting and quoted posts, by user condition (y axis: condition of the quoting user, x axis: condition of the quoted user).

users in other conditions. The amount of quotes exchanged between conditions highlights preferential discussion partners. Moreover, sentiment alignment with quoted posts reveals complex social dynamics between users in different conditions – e.g. emotionally-reinforcing or normative attitudes. This section focuses on the third research question:

**Q3** Do users in different conditions interact differently with users in other conditions?

### 7.1 Quote Volume

The number of quotes exchanged between user conditions is an index of how much attention one condition directs to and obtains from another. One way to represent quote flow is a matrix, where the $(i, j)$ element represents the number of quotes from condition $i$ to condition $j$. However, the raw data are imbalanced, due to the higher number of users in the AD condition, and their overall propensity to quote. Therefore, to gain a better sense of the proportion of quotes flowing between conditions, we rebalance the matrix by dividing it by its covariance. Figure 3 depicts the rebalanced matrix. A first observation is that the diagonal of the matrix shows higher values, meaning that **users tend to quote other users in the same condition**. Also, the strength of the interaction within one's own condition is lower for neurodiverse users. Looking at off-diagonal interactions (i.e. between different conditions), it is noteworthy that the matrix does not show clear asymmetries, which would suggest lack of reciprocation. In particular, FM users seems to interact mostly with NT and NS users.

### 7.2 Quote Sentiment Alignment

For all quotes between different conditions we compute the correlation coefficient of sentiment and fraction of words in emotional categories. This describes, within each emotional category, how aligned users in different conditions are when referring to each other. Figure 4 shows results for representative sentiment categories. In all investigated sentiment categories, when AD users quote, they always show weak-to-mild correlations ($|\rho| <= .3$) – in contrast to NT users, who show strong correlations with at least one other condition when quoting. **NT and FM users reciprocally anticorrelate in all categories but on polarity.** This means e.g. that when a FM user quotes a sad post by an NT user, the response is likely not sad, and vice versa. This behaviour also differentiates how FM and NT users reply to users in other conditions. If we look at negative sentiment and emotion words, in most cases NT users correlate positively with neurodiverse users when quoting them, "resonating" on that sentiment, while FM users correlate negatively, "counterbalancing" it.

Who users interact with reflects their condition. Specifically, users engage proportionately more with users in the same condition; neurodiverse users show less group cohesion. Also, responses to a specific emotion may reinforce it or mitigate it according to the conditions of both users involved.

## 8 Participation in Discussion

The primary purpose of an online forum is to engage users in discussion. How much one user participates in a discussion is therefore a reasonable index of how effective the forum is in delivering value to that user. This section explores what factors in a discussion are correlated with higher user participation, and if these factors differ by user condition. The following analyses consider three categories potentially cor-

**posts ~ diagnosis*posts_by_others*users**

| | coeff | p |
|---|---|---|
| diagnosis[T.AD] | 0.0596 | 0.020 |
| diagnosis[T.OA] | 0.1090 | 0.000 |
| diagnosis[T.AD]:posts_by_others | 0.4438 | 0.000 |
| diagnosis[T.OA]:posts_by_others | 0.6456 | 0.000 |
| diagnosis[T.AD]:posts_by_others:users | -0.0388 | 0.000 |
| diagnosis[T.NS]:posts_by_others:users | -0.0197 | 0.031 |
| diagnosis[T.OA]:posts_by_others:users | -0.0594 | 0.000 |

Table 4: Least-squares model with user condition, number of other users, and number of posts by others in a discussion, as predictors of how many posts the user contributes to the discussion. Interactions between all variables are included in the model. FM is the reference condition. Only significant results are shown ($p < .05$); Model $F = 597.6$ $p < .01$ $R^2 = .034$.

**log(posts) ~ diagnosis*[compound + neu + log(t_posts)]**

| | coeff | p |
|---|---|---|
| diagnosis[T.OA] | -0.3365 | 0.016 |
| compound | 0.0907 | 0.016 |
| diagnosis[T.AD]:compound | -0.1556 | 0.000 |
| log(t_posts) | 0.1010 | 0.000 |
| diagnosis[T.AD]:log(t_posts) | 0.0518 | 0.000 |
| diagnosis[T.AU]:log(t_posts) | 0.0360 | 0.000 |
| diagnosis[T.OA]:log(t_posts) | 0.0693 | 0.000 |

Table 5: Least-squares model with user condition and discussion mean sentiment polarity and charge, as predictors of how many posts the user contributes to the discussion, controlling for the number of posts in the discussion. Interactions between condition and the other predictors are included in the model. FM is the reference condition. Only significant results are shown ($p < .05$). Model $F = 2601$ $p < .01$ $R^2 = .131$.

related: the size of a discussion, since it may affect cognitive load and social exposure; the sentiment expressed in a discussion, since it may attract individuals searching for emotional support, or challenge users' emotional intelligence; and the co-presence of users in other conditions, since users in similar conditions may share interests and group identity. It must be noted that these factors are not necessarily *incentives* for user engagement, since they do not imply causality: however, they show successful scenarios of user engagement. This section answers the fourth research question:

> **Q4** Do users in different conditions contribute differently to a discussion based on its sentiment and participants?

## 8.1 Discussion Size

We compute ordinary least squares regression on the interactions between user condition, the number of other users in the discussion, and the overall number of replies by other users in the discussion, as regressors of the number of posts the user contributes to the discussion. Results are detailed in

**log(posts) ~ diagnosis*[nAD+nAU+...+t_posts]**

| | coeff | p |
|---|---|---|
| intercept | 0.2737 | 0.000 |
| diagnosis[T.NT] | 0.0702 | 0.001 |
| diagnosis[T.NS] | 0.0398 | 0.002 |
| diagnosis[T.OA] | 0.0679 | 0.000 |
| nAD | 0.0073 | 0.021 |
| diagnosis[T.AD]:nAD | -0.0075 | 0.018 |
| diagnosis[T.OA]:nAD | 0.0073 | 0.023 |
| diagnosis[T.AD]:nNT | -0.0999 | 0.021 |
| diagnosis[T.AU]:nNT | -0.1083 | 0.018 |
| diagnosis[T.OA]:nNT | -0.1382 | 0.002 |
| nAU | -0.0345 | 0.036 |
| diagnosis[T.AD]:nAU | 0.0337 | 0.040 |
| diagnosis[T.AU]:nAU | 0.0343 | 0.037 |
| diagnosis[T.NS]:nOA | -0.0301 | 0.020 |
| t_posts | 1.38e-05 | 0.003 |
| diagnosis[T.NT]:t_posts | -1.645e-05 | 0.015 |
| diagnosis[T.OA]:t_posts | 1.047e-05 | 0.028 |

Table 6: Least-squares model with user condition and the number of other users with each condition in the discussion, as predictors of how many posts the user contributes to the discussion, controlling for the number of posts in the discussion. Interactions between condition and the other predictors are included in the model. FM is the reference condition. Only significant results are shown ($p < .05$). Model $F = 481.7$ $p < .01$ $R^2 = .053$.

Table 4. AD and OA users have a positive bias in the number of posts per thread they write – however this bias was tested not significant in isolation when characterizing user contributions by condition. **AD and OA users tend to post relatively more in longer discussions**. While the sole number of other users in the discussion does not significantly affect how much they post, **the combination of both many posts and many other users in the discussion limits their rate of contribution.**

## 8.2 Discussion Sentiment

We then train a second least-squares model on the interactions of user condition, and discussion sentiment polarity and charge, controlling for the number of posts in the discussion. Like before, the outcome variable is the (log-transformed) number of posts by the user. Table 5 shows significant results. **Positively polarized discussions elicit more contributions overall; however, AD users contribute relatively less to positively polarized discussions.** Moreover, neurodiverse users post comparatively more when in longer discussions.

## 8.3 Users in Discussion

Finally, we investigate whether the co-presence of users with other conditions affects contribution. We fit a third model, regressing again the (log-transformed) number of posts. As regressors we use the interaction of the poster's condition, and the number of other users who take part in the discussion grouped by condition; furthermore, we control for the over-

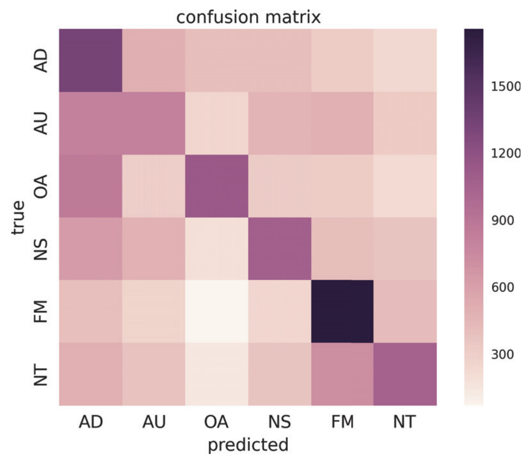


Figure 5: Confusion matrix of the predicted conditions.

| | AD | AU | OA | NS | FM | NT | *total* |
|---|---|---|---|---|---|---|---|
| **AP** | 0.42 | 0.26 | 0.36 | 0.34 | 0.55 | 0.33 | *0.375* |
| **AR** | 0.29 | 0.29 | 0.52 | 0.37 | 0.44 | 0.40 | *0.385* |
| **#** | 3191 | 3191 | 3191 | 3191 | 3191 | 3191 | *19146* |

Table 7: Average precision and recall of predictions, and number of samples, per condition and overall. The random baseline score is 16%.

all number of posts in the discussion. Results are reported in Table 6. Overall, the fraction of AD users increases the number of contributions, while that of AU decreases it. Neurodiverse users post less in co-presence with NT users. Moreover, AD users post less in co-presence with other AD users, and more in co-presence with AU. OA users, on the other hand, post relatively more in co-presence with AD users. Finally, co-presence of AU users positively correlates with posts by other AU users, while co-presence with OA users hinders posts by NS users.

This section showed that factors of user engagement in discussion differ by user condition, and replies to the final research question of this paper. The next section leverages these results assessing to what extent a classifier can discern user conditions based on characteristics of their contributions, on their interaction with other users, and on the discussions they engage in.

## 9 Classifying User Conditions

This paper analyses what characterizes users with different conditions. This section completes the description by quantifying how much they differ, giving a working proof that a classifier can predict users' conditions from their posts. Results from the previous sections inform the choice of features: sentiment and word categories (as well as their means for the user within the thread, and for the entire thread); topic proportions; content repetitions; quotes; position in the thread; post and thread length; thread views, and Gini index of the distribution of posts per user. The preprocessing step consists in imputing missing values using the mean of each feature, and appending to the feature matrix its principal components (we estimate the number through maximum likelihood) to highlight non-typical behaviour, in the spirit of (Ekblad 2013). To account for class imbalance, we take from each condition a random sample as large as the minimum number of posts in all conditions. We then evaluate a Random Forest classifier with 50 trees, and entropy as its node splitting criterion, in 10-fold cross-validation. We assign posts to folds so that all posts in a thread appear in only one fold: this is necessary since some features share the same value across the entire thread, and could otherwise provide an unfair advantage to the classifier at training time. **The classifier's mean average precision is 37%, well above the 16% random baseline** – per-condition scores are reported in Table 7. Figure 5 further shows the aggregated confusion matrix for the prediction. The classifier's errors are in line with what one would expect: it mostly mislabels AU and OA users as being AD, and NT users as FM. **When considering only users in the AD and NT conditions, the classifier scores above 75% accuracy.**

## 10 Discussion

### 10.1 Autistic Traits Online

One goal of this paper was to better understand whether autistic aspects of face-to-face communication persist in the online environment. Some of these traits indeed persist. Neurodiverse users post less emotionally charged and polarized content than neurotypical users, and resonate less with emotions in the content they respond to. These findings may explain discrepancies in the literature (Newton, Kramer, and McIntosh 2009; Nguyen et al. 2015): while there is overlap in the kind of emotions expressed by neurotypical and neurodiverse users, the associated sentiment valence and its homogeneity with the ongoing discourse show clear differences. Furthermore, neurodiverse users respond to less complex content, initiate fewer discussions, and focus more on single dialectic threads. Neurodiverse users discuss more concrete topics than neurotypical users and family members (e.g. daily tasks and relationship troubleshooting, versus considerations on autism and education), often using more reified signals (emoticons and links). Contrary to our expectations, neurodiverse users write less repeating and self-similar posts than other users - this is in contrast with the phenomena of echolalia and special interests they are typically associated with (Rouhizadeh et al. 2014).

### 10.2 Peer Support

A second goal was on quantifying the support users in different conditions experience on the forum. Neurodiverse users disclose more about themselves than neurotypical users on Wrong Planet. Therefore, users do not appear to feel stigmatized for their condition. Nonetheless, users in different conditions, especially neurotypical and family member users, are cohesive within their own group, in terms of who they reference the most in a discussion. Overall, neurotypical users and family members are referenced more than neurodiverse users, and neurotypical users receive more positive feedback than neurodiverse users when expressing negative emotions. In particular, family members and neurotypical users show patterns of mutual support, "counterbalancing" each other's negative content in replies. Neurodiverse users on the other hand seem to receive only modest emotional support from the forum.

## 11 Conclusions

The test subjects of this research are the users of a large online forum on autism who self-report their condition – e.g. having been diagnosed with Aspergers syndrome, having a family member in such a condition, being neurotypical, etc. This rich ground truth allowed fine-grained, non-obtrusive analysis of user behaviours. Users in different conditions showed distinctive patterns in the content they contribute, the discussions they engage in, and the way they interact with other users. We provided evidence of persistence of autistic traits in computer-mediated communication (with a comparison to neurotypical controls at a community scale). We obtained a novel, quantitative insight on the distinct roles that family members, neurotypical users, and users doubting their condition play in the forum. And we highlighted areas of missing integration of neurodiverse users in online forums, and factors that can influence and improve their participation, with implications not only for academics but also for community managers.

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