Mirroring Minds: Asymmetric Linguistic Accommodation and Diagnostic Identity in ADHD and Autism Reddit Communities

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Abstract

Social media research on mental health has focused predominantly on detecting and diagnosing conditions at the individual level. In this work, we shift attention to *intergroup* behavior, examining how two prominent neurodivergent communities, ADHD and autism, adjust their language when engaging with each other on Reddit. Grounded in Communication Accommodation Theory (CAT), we first establish that each community maintains a distinct linguistic profile as measured by the Linguistic Inquiry and Word Count (LIWC) dictionary. We then show that these profiles shift in opposite directions when users cross community boundaries: features that are elevated in one group's home community decrease when its members post in the other group's space, and vice versa, consistent with convergent accommodation. We further demonstrate the practical stakes of this accommodation: classifiers trained to distinguish the two communities from their in-group language lose roughly **30 percentage points** of accuracy, falling below chance, when applied to the same users' cross-community posts, confirming that accommodation, not just diagnosis, drives their predictions. Finally, in an exploratory longitudinal analysis around the moment of public diagnosis disclosure, we find that its effects on linguistic style are small and, in some cases, directionally opposite to cross-community accommodation, providing initial evidence that situational audience adaptation and longer-term identity processes may involve different mechanisms. Our findings contribute to understanding intergroup communication dynamics among neurodivergent populations online and carry implications for community moderation and clinical perspectives on these conditions.

1 Introduction

Language carries diagnostic identity, a phenomenon made observable in the pseudonymous, text-driven mental health communities of Reddit. For instance, users diagnosed with ADHD produce posts bearing measurable traces of that identity compared to a healthy person, such as decreased analytical language and increased markers of raw authenticity (Mankarious et al., 2025). On the other hand, those diagnosed with autism leave a different trace: increased social references and increased emotional tones (Mankarious et al., 2025; Fong et al., 2025). These are not stereotypes but statistical regularities that emerge robustly across thousands of users and hundreds of thousands of posts. Yet our understanding of what happens to these identity-linked markers when a user steps outside their home community remains limited.

Addressing this gap requires bridging two research traditions that have largely developed in isolation. The first is the computational analysis of mental health in social media, which has produced a rich literature on detecting and characterizing conditions at the individual level (Chancellor and De Choudhury, 2020). Although this body of work has been enormously productive, it has overwhelmingly treated users as isolated data points rather than members of dynamic communities; consequently, the macro-level dynamics of how users communicate across community boundaries remain theoretically unaccounted for. The second tradition is Communication Accommodation Theory (CAT; Giles and Soliz, 2015), which has a decades-long tradition of studying how people adjust their communicative style, converging toward, diverging from, or maintaining their style, in response to social context and identity goals. While CAT has demonstrated remarkable explanatory power across decades of research, it has been applied predominantly in face-to-face intergroup contexts (Zhang and Giles, 2017), leaving its potential as a macro-level framework for understanding dynamic communicative behavior across digital community boundaries largely untapped. Recent

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work validating CAT in online settings (Danescu-Niculescu-Mizil et al., 2011; Boghrati et al., 2018; Tamburrini et al., 2015) and extending it to affective dimensions (Bernhold and Giles, 2022) suggests the theory is well positioned to fill precisely the gap the first tradition leaves open.

The gap matters for a concrete reason. Online neurodivergent communities are among the largest and most active mental health spaces on the internet. On Reddit alone, r/ADHD and r/autism together host millions of subscribers who use these spaces not just for information exchange but for identity construction, peer support, and diagnostic sense-making (Rideout and Robb, 2021) Members of these communities regularly cross-post: an ADHD-diagnosed user may seek advice in r/autism, or an autism-diagnosed user may share experiences in r/ADHD. When they do, they face an implicit communicative choice: maintain their own group's linguistic style, or adapt to the norms of the host community.

The stakes of this communicative choice are not merely social; they directly undermine the computational tools built to study these communities. A large body of work trains classifiers to distinguish neurodivergent conditions from social media language (Chancellor and De Choudhury, 2020). But if a user's measured linguistic profile shifts with their audience, such a classifier may be learning the signature of a *community* rather than of a *condition*. We test this directly in a motivating experiment (Section 4.1): classifiers trained to separate ADHD from autism users on their in-group posts reach 66–68% accuracy, but the same models, applied to the same users' cross-community posts, collapse to 36–37%, below chance, a $\sim$30-point drop that is statistically significant and consistent across logistic regression, linear SVC, and random forest. Accommodation, in other words, is not a nuisance to be denoised away; it actively determines what these models predict. This finding both motivates and frames the present study: to understand why diagnostic classifiers fail across community boundaries, we must first characterize the distinct community styles (H1) and the accommodation that operates between them (H2).

To analyze how these two groups communicate on Reddit using CAT lens, we adopt following framework, Grounded in CAT and the prior work reviewed above:

H1 (Distinct Baseline Styles) ADHD and autism communities exhibit measurably distinct linguistic profiles when posting in their respective home communities.

H2 (Cross-Community Convergence) When users post in the other community, their linguistic style shifts toward the host community's baseline, consistent with convergent accommodation.

H3 (Classifier Vulnerability) Because diagnostic classifiers trained on in-group language anchor on community-specific stylistic norms rather than condition-intrinsic traits, their accuracy degrades sharply, dropping below chance, when the same users post across community boundaries.

RQ (Diagnosis Disclosure) Does public disclosure of a diagnosis produce within-user linguistic changes, and if so, are these changes consistent with, independent of, or opposed to the situational accommodation captured in H2? We treat this as exploratory given the inherent power limitations of longitudinal within-user analysis.

Contributions. Our work makes the following contributions:

- We provide the first study of cross-community linguistic accommodation between neurodivergent groups on social media, shifting the focus from individual-level diagnosis detection to intergroup behavioral dynamics.
- We establish distinct linguistic profiles for ADHD and autism communities and demonstrate that these profiles undergo systematic, bidirectional shifts when users cross community boundaries, with medium effect sizes and a mirror-image pattern across multiple LIWC dimensions.
- We demonstrate a concrete consequence of this accommodation for computational mental health: diagnostic classifiers that distinguish the two communities on in-group posts lose roughly 30 absolute points of accuracy, collapsing to below chance, when applied to the same users' cross-community posts, an algorithm-agnostic vulnerability that reframes such "noise" as a measurable social strategy.

- We present an exploratory longitudinal analysis of pre-/post-diagnosis linguistic changes, finding initial evidence that situational accommodation and identity-related shifts may operate through different mechanisms, though the small effect sizes warrant cautious interpretation.

2 Data

2.1 Source Dataset

We draw on the Mindset dataset (Mankarious et al., 2025), a recently released Reddit corpus in which users are identified via high-precision self-reported diagnosis. Mindset implemented rigorous filtering to ensure label quality, including excluding weak diagnosis statements (e.g., "I have adhd", "I think I have adhd") in favour of stronger statements (e.g., "My doctor diagnosed me with ADHD"), and excluding negated diagnoses (e.g., "... did not diagnose..."). In the absence of clinically validated ground truth, we adopt self-diagnosis labels as ground, consistent with the literature (Cohan et al., 2018; Coppersmith et al., 2015; Mankarious and Zirikly, 2025; Mankarious et al., 2025; Ernala et al., 2019).

From Mindset, we selected the ADHD and autism groups. Because our analysis requires cross-community posting, we did not use Mindset's preprocessed posts directly, which are heavily filtered to remove mental health content. Instead, we re-fetched each user's full posting history from Reddit using the same API[1], retaining posts that include mental health discussions necessary for the accommodation analysis. We additionally collected metadata including interaction scores and parent post identifiers.

2.2 Cross-Community Partitioning

To operationalize accommodation, we partitioned the data into four subsets based on the user's diagnostic group and the subreddit in which they posted (Table 10): *ADHD in ADHD* (posts by ADHD-diagnosed users in r/ADHD), *ADHD in Autism* (posts by ADHD-diagnosed users in r/autism), and the symmetric pair for autism-diagnosed users. This subreddit-based partitioning is motivated by two considerations: (1) the vast majority of each group's contributions are concentrated in these two subreddits, and (2) keyword-based topic filtering would be unreliable, since discussions in either subreddit frequently touch on the other condition. We verified that no users appear in both diagnostic groups, ensuring that the four subsets represent cleanly separated populations.

2.3 Preprocessing

We excluded posts that had been removed by moderators or that contained fewer than five words after tokenization, as these are unlikely to carry sufficient stylistic signal for LIWC analysis.

3 Experiments

3.1 Linguistic Feature Extraction

We processed all posts through LIWC-22 (Boyd et al., 2022), extracting scores across 115 categories spanning psychological processes, linguistic dimensions, and summary variables. To account for pseudoreplication, the inflation of statistical significance when multiple posts from the same user are treated as independent observations, we aggregated all LIWC scores at the *user* level by averaging across each user's posts within each condition (Walls and Schafer, 2006). This ensures that each user contributes a single data point per analysis, yielding conservative but reliable estimates.

Several LIWC categories carry technical meanings that diverge from their everyday connotations; Table 1 defines the ones whose interpretation is least intuitive, and Appendix G (Table 11) defines every category featured in our figures and tables. Crucially, LIWC scores are word-frequency rates rather than measures of communicative intent: a high SOCIAL score reflects how often a user *writes about* social matters, not how socially engaged they are, and a high AUTHENTIC score reflects a spontaneous, first-person style rather than any judgment of honesty.

3.2 Statistical Methodology

All group comparisons use Welch's t-test (unequal variances) with Cohen's d as the effect size measure, accompanied by 95% confidence intervals computed via the noncentral t-distribution (see Appendix F for details). Following Benjamini and Hochberg (1995), we apply the Benjamini–Hochberg procedure to control the false discovery rate (FDR) at $q = 0.05$ within each experiment, correcting for the 115 simultaneous tests across LIWC categories. Only categories that remain significant after FDR correction are reported. We adopt stan-

[1] https://github.com/ArthurHeitmann/arctic_shift

Table 1: LIWC categories whose technical meaning most diverges from everyday usage. Scores are word-frequency rates, not measures of intent. † marks *summary variables*. The full glossary of all featured categories is in Appendix G (Table 11).

Category	One-line definition
AUTHENTIC†	Spontaneous, first-person style (more *I/me*, fewer hedges); not a measure of honesty.
CLOUT†	Confident, authoritative stance (more *we/you*, fewer *I*); social standing, not actual influence.
SOCIAL	Words about people and social processes; *writing about* social matters, not social engagement.
SOCREFS	References to other people (*they*, *you*, names); mentions, not actual interaction.

dard effect size thresholds: $|d| < 0.20$ negligible, $0.20 \leq |d| < 0.50$ small, $0.50 \leq |d| < 0.80$ medium, $|d| \geq 0.80$ large (Cohen, 1988).

3.3 Operationalizing Accommodation

Classical CAT measures accommodation at the conversational level: speaker A adjusts toward speaker B within a specific exchange. In asynchronous online communities, direct pairing is not always possible. Following Danescu-Niculescu-Mizil et al. (2011) and Tamburrini et al. (2015), we measure *community-level convergence*: whether the same user's linguistic profile shifts toward the host community's aggregate norms when posting in a different subreddit. This within-user design means each user serves as their own control, ruling out subpopulation confounds. The critical evidence for *accommodation* rather than mere *change* is directionality: ADHD users decrease on ADHD-high features and increase on autism-high features when visiting r/autism, and autism users show the exact mirror pattern. Random variation or topic effects would not produce this symmetric, baseline-aligned pattern across multiple independent LIWC categories.

3.4 Motivating Experiment: Classifier Vulnerability under Accommodation (H3)

Before turning to the CAT analysis, we establish the practical stakes of accommodation with a cross-community classification experiment that directly tests **H3**. The standard computational paradigm trains a model to distinguish diagnostic groups from their in-group language; we ask whether such a model survives contact with the same users' cross-community language.

Setup. We define two evaluation environments. The *in-group* (baseline) set comprises posts by ADHD users in r/ADHD (class 0) and autism users in r/autism (class 1), the standard diagnostic-classification setting. The *cross-community* (out-group) set comprises posts by the *same* users in the other community: ADHD users in r/autism (class 0) and autism users in r/ADHD (class 1). Each post is represented by 13 LIWC categories that distinguish the two communities (TIME, ACHIEVE, AUTHENTIC, WORK, SOCREFS, SUBSTANCES, ACQUIRE, SOCIAL, THEY, CLOUT, TONE, I, HEALTH; cf. E1), standardized (z-scored) using statistics fit exclusively on training folds.

Protocol. To prevent user leakage, we use 5-fold `GroupKFold` cross-validation grouped by username, so no user appears in both the training and test sets. In each fold we (1) train on the in-group posts of the training users, (2) evaluate on the in-group posts of the held-out users (baseline diagnostic accuracy), and (3) evaluate on the cross-community posts of those *same* held-out users (robustness to accommodation). We test three algorithm families, logistic regression, linear SVC, and random forest, all with balanced class weights, to assess whether any vulnerability is algorithm-agnostic. We report mean accuracy across folds and test the per-fold accuracy drop with a paired t-test.

3.5 Experiment 1: Baseline Linguistic Styles (H1)

To test H1, we compared diagnosed ADHD users posting in their home community (r/ADHD, $n =$ 7,758 users) against diagnosed autism users posting in their home community (r/autism, $n =$ 5,706 users). This between-group comparison characterizes the distinct baseline stylistic profiles against which accommodation effects can be measured.

3.6 Experiment 2: Cross-Community Accommodation (H2)

To test H2, we conducted within-group comparisons of each diagnostic group's language when posting in their home community versus the other community:

- ADHD users: language in r/ADHD (in-group) vs. r/autism (out-group)

- Autism users: language in r/autism (in-group) vs. r/ADHD (out-group)

If convergent accommodation occurs, we expect shifts in the direction of the host community's baseline for categories identified in E1. We additionally examine whether the two groups' shifts are *mirror images*, that is, whether categories that shift upward for one group shift downward for the other. See appendix E for a discussion on potential selection bias in this experiment.

3.7 Experiment 3: Exploratory Longitudinal Analysis (RQ)

To address the exploratory research question, we conducted within-user paired comparisons of language use before and after each user's first public diagnosis disclosure. This analysis is restricted to users who have posts in both pre- and post-disclosure periods within a given cross-community dataset (≥ 3 posts in each period). The temporal structure of user activity varies across datasets; see Appendix D (Table 9) for average pre- and post-diagnosis posting spans. By comparing E3 effect sizes against E2 effect sizes for the same categories, we assess whether diagnosis disclosure produces changes that are consistent with, independent of, or opposed to situational accommodation. We emphasize that this analysis is exploratory: the within-user design reduces sample sizes substantially, and the resulting effect sizes should be interpreted with appropriate caution.

4 Results

4.1 Motivating Experiment: Classifier Vulnerability (H3)

Table 2 reports the outcome. On in-group data, all three models distinguish ADHD from autism posts at 66.0–67.6% accuracy. Applied to the *same held-out users'* cross-community posts, accuracy collapses to 36.0–37.4%, below the 50% chance baseline, a $\sim$30 percentage-point drop that is highly significant for every model ($p < 10^{-5}$, paired t-test across folds). Because the GroupKFold design rules out memorization of individual users, and because the collapse is near-identical across linear (logistic regression, linear SVC) and ensemble (random forest) decision boundaries, the vulnerability is algorithm-agnostic.

This result supports **H3** and motivates the remainder of the paper: the classifiers anchor on the linguistic norms of the *community environment* rather than condition-intrinsic traits, so when users accommodate to a new community the in-group decision boundary fails systematically, even inverting below chance. The two experiments that follow explain why, by characterizing the distinct community styles (E1) and the bidirectional accommodation between them (E2).

4.2 E1: Baseline Stylistic Differences (H1)

Table 3 presents the 10 LIWC categories with the largest absolute effect sizes between ADHD users in r/ADHD ($n = 7{,}758$) and autism users in r/autism ($n = 5{,}706$).

Across 115 LIWC categories, user-level comparison revealed small-to-medium effect sizes (maximum $|d| = 0.76$). ADHD users scored higher on TIME ($d = 0.76$), ACHIEVE ($d = 0.60$), and AUTHENTIC ($d = 0.59$), while autism users scored higher on SOCREFS ($d = -0.56$), SOCIAL ($d = -0.52$), and THEY ($d = -0.45$). All confidence intervals are narrow and exclude zero, confirming reliable between-group differences. These directions are independently attested in prior research: ADHD self-disclosure is marked by distinctive patterns around achievement, temporal orientation, and self-reference (Guntuku et al., 2019), matching the TIME, ACHIEVE, and AUTHENTIC elevations we observe, while autism discourse is characterized by elevated social references (Fong et al., 2025; Boorse et al., 2019), matching the SOCREFS, SOCIAL, and THEY elevations. These results support **H1**: the two communities maintain distinct and measurable linguistic profiles in their home communities, consistent with prior work on these populations' language patterns (Lyons et al., 2018). The full set of 15 significant categories is reported in Appendix B.

4.3 E2: Cross-Community Accommodation (H2)

Table 4 summarizes the categories with the largest bidirectional shifts. When ADHD users posted in r/autism, they showed decreased AUTHENTIC ($d = -0.61$) and TIME ($d = -0.70$), and increased SOCIAL ($d = +0.44$) and CLOUT ($d = +0.43$). When autism users posted in r/ADHD, the pattern reversed: increased AUTHENTIC ($d = +0.33$) and TIME ($d = +0.43$), decreased SOCIAL ($d = -0.47$) and CLOUT ($d = -0.31$). In each case, the shift direction aligns with the host community's baseline from E1.

As discussed in Section 3.3, the evidence for

Table 2: Motivating experiment: mean classification accuracy across 5 user-isolated (GroupKFold) folds. Models are trained on in-group posts and evaluated on both the in-group and the cross-community posts of held-out users. The accuracy drop is the penalty for evaluating out-group posts; all drops are statistically significant ($p < 0.001$, paired t-test across folds).

Model	**In-group Acc.**	**Cross-community Acc.**	**Accuracy Drop**	**p-value**
Logistic Regression	66.01%	36.16%	−29.85%	2.0×10^{-6}
Linear SVC	65.67%	35.98%	−29.69%	1.9×10^{-6}
Random Forest	67.60%	37.37%	−30.22%	9.0×10^{-7}

Table 3: Baseline linguistic differences (E1, top 10). Category definitions in Table 11.

Category	**ADHD**	**Autism**	**d [95% CI]**
time	5.62	3.93	0.76 [.72, .80]
achieve	1.59	0.95	0.60 [.56, .64]
Authentic	78.4	69.4	0.59 [.55, .63]
work	2.09	1.26	0.58 [.54, .62]
socrefs	5.05	6.68	−0.56 [.52, .60]
substances	0.46	0.05	0.55 [.51, .59]
acquire	1.29	0.83	0.53 [.49, .57]
Social	8.99	11.3	−0.52 [.48, .56]
they	0.59	0.94	−0.45 [.41, .49]
Lifestyle	3.19	2.35	0.45 [.41, .49]

All FDR-corrected ($q < 0.05$). $+d$: higher in ADHD; $-d$: higher in autism. CIs report absolute $|d|$ bounds.

Table 4: Cross-community accommodation (E2). Category definitions in Table 11.

Category	**ADHD→Aut.** d [95% CI]	**Aut.→ADHD** d [95% CI]
Authentic	−.61 [.53,.69]	+.33 [.29,.37]
time	−.70 [.62,.78]	+.43 [.39,.47]
Social	+.44 [.36,.52]	−.47 [.43,.51]
Clout	+.43 [.35,.51]	−.31 [.27,.35]
socrefs	+.45 [.37,.53]	−.47 [.43,.51]
i	−.37 [.29,.45]	+.11 [.07,.15]
health	−.25 [.17,.33]	+.44 [.40,.48]

All FDR-corrected ($q < 0.05$). Every category shifts in opposite directions for the two groups. CIs report absolute $|d|$ bounds.

accommodation is this mirror-image directionality, which holds across eight categories (Table 6). The two largest effects involve AUTHENTIC and CLOUT, which are topic-independent summary variables [2] (Appendix H), providing some reassurance against a purely topical explanation. Effect sizes are small-to-medium ($|d| = 0.31$–0.70). Importantly, these categories are not merely selected for their bidirectional symmetry: they are also among the largest-magnitude shifts overall within each group, ranking near the top across all 115 LIWC dimensions rather than constituting a hand-picked subset of small effects (for ADHD users visiting r/autism, TIME and AUTHENTIC are the two largest shifts of any category). The convergent pattern therefore reflects the dominant axes of each group's adaptation. These results support **H2**. Figure 1 visualizes the pattern; a quantitative summary is in Appendix A.

[2] Authentic category captures honest, personal language such as 'me', 'my', 'but' etc, indicating careful cognitive processing. Clout category captures a speaker's standing within a social hierarchy, indicated by use of terms such as first person plural 'we', 'us' (high clout) and first person singular 'i' (low clout)

4.4 E3: Exploratory Longitudinal Analysis (RQ)

We conducted within-user paired comparisons of language use before and after diagnosis disclosure. The full results are reported in Appendix D; we summarize the key findings here.

The effects are uniformly small ($|d| \leq 0.22$) with wide confidence intervals. For ADHD users posting in r/autism, only HEALTH ($d = -0.22$) and PREP ($d = -0.20$) changed significantly, with no changes for AUTHENTIC or CLOUT. For autism users posting in r/ADHD, diagnosis disclosure was associated with decreased AUTHENTIC ($d = -0.12$) and increased CLOUT ($d = +0.11$), notably, in the *opposite* direction from the E2 accommodation pattern for these same categories.

Addressing **RQ**: diagnosis disclosure is associated with detectable within-user changes, but the effects are weak and should be interpreted as preliminary. Table 8 (Appendix D) compares E2 and E3 effect sizes for key categories, showing that accommodation effects are consistently 3–23× larger than post-diagnosis changes.

4.5 Summary

H1 is well supported: the two communities maintain distinct baseline linguistic profiles (medium effect sizes, narrow CIs). **H2** is supported: both groups converge toward the host community's norms when cross-posting, with a systematic mirror-image pattern that is difficult to attribute to topic effects alone (medium effect sizes). **H3** is strongly supported: diagnostic classifiers trained on in-group language suffer a large, algorithm-agnostic accuracy collapse (∼30 points, to below chance) when evaluated on the same users' cross-community posts, confirming that accommodation, not just diagnosis, drives their predictions. The exploratory **RQ** yields initial but inconclusive evidence: diagnosis disclosure produces small and sometimes directionally opposite effects relative to situational accommodation.

5 Related Work

5.1 Communication Accommodation Theory

Communication Accommodation Theory (CAT) provides a foundational framework for understanding how individuals adjust their communication styles in social interactions (Giles, 1973). CAT posits that speakers may either converge toward their interlocutor's style to seek approval or diverge to emphasize distinctiveness. The theory has been widely applied across contexts, including psychotherapy, where accommodation patterns reflect therapeutic rapport and power dynamics (Ferrara, 1991).

5.2 CAT in Social Media and Online Communities

Recent work has extended CAT to digital contexts, particularly social media platforms where interaction patterns are publicly observable. Danescu-Niculescu-Mizil et al. (2011) developed a rigorous framework for measuring linguistic accommodation on Twitter, demonstrating that users adapt their language to align with conversational partners. Their approach focused on function words as stylistic markers and introduced probabilistic methods to isolate accommodation from topic-driven similarity. On Reddit, Boghrati et al. (2018) showed that commenters systematically accommodate to the syntactic style of original posts, providing evidence for accommodation across diverse interactional contexts. Tamburrini et al. (2015) found that members of online communities converge in their linguistic practices over time, and Kovács and Kleinbaum (2021) showed that affective convergence follows a similar pattern within communities. Of direct relevance to our work, Sharma and De Choudhury (2018) examined accommodation across 55 Reddit mental health communities, finding a positive relationship between the degree of accommodation exhibited in posts and the level of social support received. However, most of this work has examined accommodation *within* a single community or between pairs of interlocutors. Our work differs by examining accommodation *across* two distinct communities, specifically, what happens when a member of one diagnostic community posts in the other's space.

5.3 LIWC and Mental Health Discourse

Linguistic Inquiry and Word Count (LIWC) has been widely employed to characterize mental health discourse in online communities (Pennebaker et al., 2015). Lyons et al. (2018) analyzed language patterns across multiple mental health conditions on discussion forums, identifying distinctive linguistic markers associated with various conditions. Within autism research, LIWC has been used to identify subtle language differences in narrative production (Boorse et al., 2019). ADHD communities have been less studied linguistically, though work on ADHD self-disclosure suggests that these users employ distinctive patterns around achievement, temporal orientation, and self-reference (Guntuku et al., 2019). A growing body of work uses NLP to detect mental health conditions from social media text (Chancellor and De Choudhury, 2020), but this line of research treats users as isolated individuals rather than members of interacting communities. Our work extends this by comparing ADHD and autism communities directly, both in baseline styles and accommodation patterns.

5.4 Identity, Disclosure, and Mental Health on Reddit

The moment at which an individual publicly discloses a mental health diagnosis has been recognized as a pivotal identity event in both clinical and social-psychological literature (Corrigan et al., 2015). Reddit has emerged as a valuable source for studying mental health discourse due to its anonymous, community-based structure (De Choudhury and De, 2014). On Reddit, self-disclosure of a diagnosis often functions as an identity claim that restructures how an individual participates in community discourse (De Armond et al., 2020). More recently, researchers have examined identity formation and disclosure processes in neurodivergent populations, highlighting the developmental trajectory of diagnostic identity (DePape et al., 2025) and how autism social identification predicts disclosure behaviors (Togher et al., 2023). Prior work has examined how disclosure affects reception by others, but less attention has been given to how it changes the discloser's own linguistic behavior over time. Our longitudinal analysis addresses this gap.

6 Discussion

This study applied Communication Accommodation Theory to intergroup linguistic dynamics between ADHD and autism communities on Reddit. The two communities maintain distinct baseline profiles (H1), and users' language converges toward the host community in a mirror-image pattern when crossing boundaries (H2). This accommodation carries a concrete computational cost: in-group classifiers lose $\sim$30 points of accuracy, falling below chance, on the same users' cross-community posts (H3). By contrast, public diagnosis disclosure produced only small and sometimes directionally opposite changes (RQ, $|d| \leq 0.22$), initial evidence that situational and identity-related processes differ, though these small effects warrant cautious interpretation.

To move beyond atheoretical description of these macro-level patterns, we propose a *neuro-intercultural lens* that extends CAT's intercultural encounter model (Giles, 2016) to neurodivergent communities, treating them as distinct cultural groups rather than collections of clinical symptoms. The individualism/collectivism dimension (Zhang and Giles, 2017) offers a coherent account of the observed asymmetry: the ADHD community's higher AUTHENTIC scores and $4\times$ higher cross-posting rate align with an individualist, socially permeable orientation, whereas the autism community's higher CLOUT and tighter boundaries reflect a collectivist one in which accommodation functions as a strategic social passport. Under this view, cross-community accommodation is not a byproduct of topic change but a means by which users negotiate social identity and group membership through discursive choices, extending CAT's mechanisms to digitally mediated neurodivergent communities.

These dynamics are further contextualized by recent evidence of macro-level semantic convergence between the two communities: (Kang et al., 2025) report that r/ADHD and r/autism have shifted from distinct topical enclaves toward shared adult-centric concerns such as employment and formal diagnosis. As topics converge, the remaining distinctions become primarily stylistic, making accommodation more salient as a navigational strategy. Notably, the 'steeper' semantic alignment of ADHD discourse toward autism that they report is consistent with our finding that r/ADHD is the more permeable host, corroborating its individualist, outgroup-open orientation relative to the more boundary-conscious autism community.

Practical implications. Community norms appear to shape language even for visitors from other diagnostic groups, which may be relevant for designing inclusive cross-community spaces. The finding that accommodation is primarily situational suggests that cross-community engagement does not fundamentally alter how users communicate in their home communities.

Implications for clinical understanding. The distinct profiles we identify align with recognized communicative differences between ADHD and autism (Lyons et al., 2018), but users flexibly adjust these markers across community boundaries, so a group's "characteristic" language may be more context-dependent than assumed. If the lexical features that distinguish diagnostic groups are the same ones that shift under social pressure (Ait Hou et al., 2026), classifiers trained on in-community data may be unreliable in cross-community or mixed-audience settings, a degradation our motivating experiment demonstrates directly (Section 4.1).

Theoretical implications. High reported accuracies for subreddit-based mental-health classification (Kim et al., 2020) thus face a significant boundary: the $\sim$30-point collapse from in-group to cross-community evaluation (Table 2) shows such accuracy is substantially an artifact of community environment rather than a measurement of the condition. When a user converges toward a community's norms, a static detector may misread this situational alignment as the underlying condition. Reframed through CAT, what is often treated as classification noise is a social strategy, suggesting mental-health informatics should model not only what a user says but the audience they are adapting to.

Limitations

Several limitations should be considered when interpreting these results.

First, our design cannot fully disentangle stylistic accommodation from topical adaptation. When an ADHD user posts in r/autism, they likely discuss different content, which could drive some LIWC shifts. The involvement of topic-independent summary variables (AUTHENTIC, CLOUT) and the within-user design provide partial mitigation, but future work should conduct topic-controlled replications, such as matching posts by topic cluster before computing LIWC differences, and compare cross-posters against non-cross-posters at baseline to rule out selection bias (see Appendix E for a proposed methodology).

Second, diagnosis labels were derived from self-disclosed statements in Reddit posts rather than confirmed clinical diagnoses (Mankarious et al., 2025). While self-disclosure is an accepted method in social media mental health research, it may introduce misclassification if users speculate about or misrepresent their diagnostic status.

Third, our analysis is limited to two neurodivergent communities on a single platform and may not generalize to other conditions or offline contexts. Fourth, the longitudinal analysis assumes the disclosure timestamp approximates diagnosis timing; delays may blur the pre-/post-boundary. Fifth, user-level aggregation reduces statistical power, and LIWC captures only lexical phenomena, future work should incorporate syntactic, embedding-based, and discourse-level features. Sixth, our between-group baseline (E1) compares the ADHD and autism communities to each other but not to a neurotypical control; without a non-clinical reference condition, we cannot determine whether an elevated category reflects one group scoring above typical levels or the other scoring below. Applying the same pipeline to a matched general-population sample is an important next step for localizing the source of each difference.

Ethical Considerations

This study analyzes publicly available Reddit posts from users who self-disclosed mental health diagnoses. We report no individual-level data, usernames, or verbatim content. All analyses are aggregate-level. We use labels from the Mindset dataset (Mankarious et al., 2025) and do not assign diagnoses. We acknowledge the risk that analysis of neurodivergent communication could be misused to stigmatize; our intent is to understand intergroup dynamics and inform inclusive platform design.

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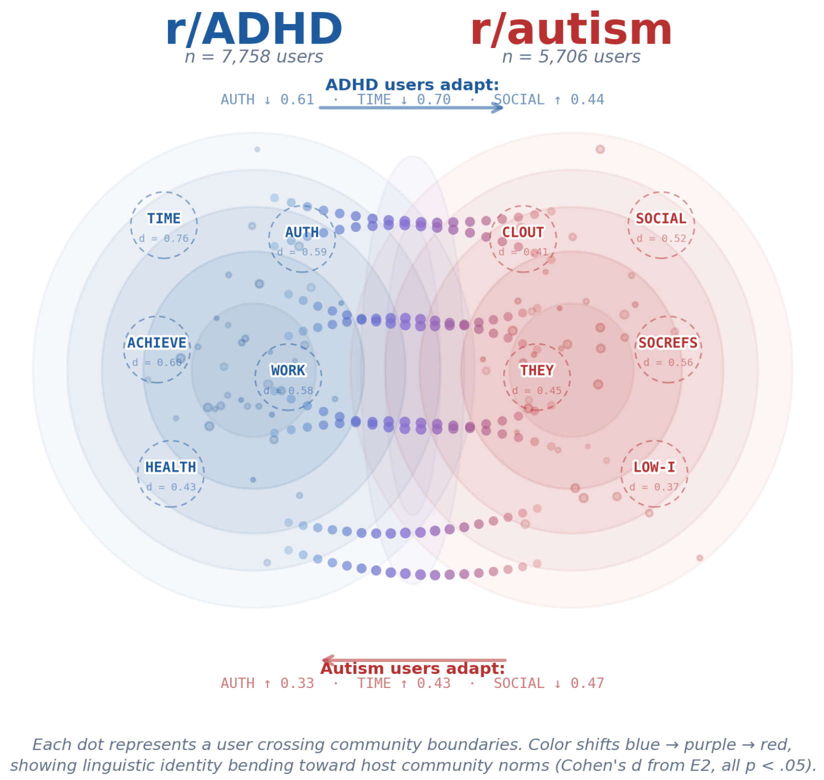

Figure 1: Bidirectional linguistic accommodation between neurodivergent Reddit communities. Each dot represents a user crossing community boundaries. r/ADHD (blue, $n = 7{,}758$): higher TIME, AUTHENTIC, ACHIEVE, WORK. r/autism (red, $n = 5{,}706$): higher SOCIAL, SOCREFS, CLOUT, THEY. Color shifts (blue $\rightarrow$ purple $\rightarrow$ red) represent accommodation toward host norms. See Table 11 for category definitions and Appendix H for detailed results.

A Quantitative Summary of All Experiments

Figure 2 provides a three-panel quantitative summary. Panel (a) shows baseline stylistic differences (E1), panel (b) visualizes the mirror-image accommodation shifts (E2), and panel (c) compares E2 and E3 effect sizes, showing that situational accommodation is 3–23$\times$ stronger than post-diagnosis identity changes.

B Full Baseline Differences (E1)

Table 5 reports the 15 LIWC categories with the largest absolute effect sizes from E1. These organize into three interpretive clusters. *Temporal and goal-oriented language*: ADHD users score higher on TIME (d=0.76), ACHIEVE (d=0.60), and WORK (d=0.58), consistent with ADHD's heightened temporal awareness and goal-directed urgency (Lyons et al., 2018) and with prior reports of achievement- and temporally-oriented language in ADHD self-disclosure (Guntuku et al., 2019). *Social orientation*: Autism users score higher on SOCREFS (d=-0.56), SOCIAL (d=-0.52), THEY (d=-0.45), and CLOUT (d=-0.41), reflecting the community's focus on navigating social relationships and matching the elevated social references previously documented in autism discourse (Fong et al., 2025; Boorse et al., 2019). *Self-presentation*: ADHD users score higher on AUTHENTIC (d=0.59), indicating spontaneous self-expression consistent with the heightened markers of raw authenticity reported for ADHD (Mankarious et al., 2025; Guntuku et al., 2019), while autism users' higher CLOUT reflects more authoritative language. Both are LIWC summary variables designed to be topic-independent.

C Mirror-Image Accommodation

Table 6 aligns E1 baselines with E2 shift directions. For every category, features that are high for a group at baseline decrease when that group visits the other community, and vice versa, the defining signature of convergent accommodation. This includes THEY, the third-ranked autism-skewed category at baseline (Table 5): autism-diagnosed users reduce their use of THEY when posting in r/ADHD and ADHD-diagnosed users increase it

Table 5: Baseline differences (E1, top 15 by $|d|$).

Category	ADHD	Autism	d
time	5.621	3.929	0.76
achieve	1.585	0.950	0.60
Authentic	78.41	69.37	0.59
work	2.091	1.255	0.58
socrefs	5.047	6.682	−0.56
substances	0.462	0.050	0.55
acquire	1.293	0.833	0.53
Social	8.987	11.33	−0.52
they	0.588	0.937	−0.45
Lifestyle	3.185	2.350	0.45
health	3.120	2.179	0.43
Clout	19.96	26.62	−0.41
quantity	4.306	3.544	0.41
focuspast	4.423	3.563	0.40
prep	12.13	11.07	0.39

All FDR-corrected ($q < 0.05$). $+d$: ADHD higher; $-d$: autism higher.

when posting in r/autism, the same convergent pattern observed for the other categories.

Table 6: E1 baseline direction vs. E2 shift direction.

Category	Higher at E1	ADHD→Aut.	Aut.→ADHD
Authentic	ADHD	↓	↑
time	ADHD	↓	↑
Social	Autism	↑	↓
Clout	Autism	↑	↓
socrefs	Autism	↑	↓
they	Autism	↑	↓
health	ADHD	↓	↑
i	ADHD	↓	↑

Every shift moves toward the host community's baseline.

D Longitudinal Analysis (E3)

Table 7 reports all significant within-user changes after diagnosis disclosure. Three observations stand out: (1) only 2 of 115 categories change for ADHD users and 6 for autism users, disclosure does not broadly reshape linguistic style; (2) all effects are small ($|d| \leq 0.22$), compared to medium effects in E2 ($|d| = 0.31$–0.70); (3) for autism users in r/ADHD, the post-diagnosis direction for AUTHENTIC (d=-0.12) and CLOUT (d=$+0.11$) is *opposite* to the E2 accommodation direction (d=$+0.33$ and d=-0.31), suggesting that identity consolidation and situational accommodation may pull in different directions.

Table 8 places these post-diagnosis (E3) effects alongside the situational accommodation (E2) effects for the same categories, showing that accommodation is consistently 3–23× larger and, for AUTHENTIC and CLOUT in the Aut.→ADHD condition, directionally opposite.

D.1 Timeline of User Activity

To contextualize the pre-/post-diagnosis split, Table 9 reports average temporal distances between users' first post, diagnosis disclosure, and final post. ADHD users in r/autism show the shortest pre-diagnosis window ($M = 52$ days), while autism users in r/ADHD show the longest ($M = 304$ days), suggesting that autism-diagnosed users participate in ADHD spaces well before disclosing their diagnosis.

E Proposed Robustness Analyses

The E2 accommodation results face two key threats to validity: (1) cross-posters may differ systematically from non-cross-posters at baseline (*selection bias*), and (2) LIWC shifts may reflect topical rather than stylistic adaptation (*topic confound*). We describe the methodology for addressing each and discuss what the current design already controls for.

Cross-posting rates and asymmetry. Of 7,758 ADHD-diagnosed users, 788 (10.2%) also posted in r/autism. Of 5,706 autism-diagnosed users, 2,305 (40.4%) also posted in r/ADHD. This ∼4× asymmetry likely reflects ADHD–autism comorbidity rates (estimated 30–80% clinically), r/ADHD's larger subscriber base (>1.8M vs. >400K), and possible differences in community openness.

Selection bias test. We compared in-community LIWC profiles (home subreddit only) of cross-posters vs. non-cross-posters within each group: ADHD cross-posters (n=788) vs. non-cross-posters (n=6,970), and autism cross-posters (n=2,305) vs. non-cross-posters (n=3,401). If cross-posters already exhibit profiles shifted toward the other community's norms *before visiting it*, the E2 effects may partly reflect who chooses to cross-post rather than how they adapt. Conversely, if cross-posters and non-cross-posters are linguistically indistinguishable in their home community, this strengthens the audience-adaptation interpretation. We note that even if cross-posters differ at baseline, the within-user E2 design (comparing each user's own home vs. cross-community posts) partially controls for this, since any baseline difference is constant within a user.

Table 7: Longitudinal changes after diagnosis disclosure (exploratory E3).

Dataset	Category	Pre	Post	Shift	d	95% CI
ADHD in Aut.	health	2.45	1.65	−0.80	−0.22	[−.36, −.08]
	prep	11.12	10.25	−0.87	−0.20	[−.34, −.06]
Aut. in ADHD	Authentic	77.22	74.21	−3.00	−0.12	[−.20, −.04]
	Clout	19.30	22.12	+2.82	+0.11	[+.03, +.19]
	i	8.81	8.30	−0.51	−0.11	[−.19, −.03]
	they	0.59	0.69	+0.11	+0.10	[+.02, +.18]
	health	3.09	3.45	+0.36	+0.09	[+.01, +.17]
	socrefs	4.85	5.26	+0.41	+0.08	[+.00, +.16]

FDR-corrected ($q < 0.05$). All effects small to negligible ($|d| \leq 0.22$).

Table 8: E2 (accommodation) vs. E3 (post-diagnosis) effect sizes. Category definitions in Table 11.

Category	Dataset	E2 d	E3 d
Authentic	ADHD→Aut.	−0.61	−0.09
	Aut.→ADHD	+0.33	−0.12
Clout	ADHD→Aut.	+0.43	+0.11
	Aut.→ADHD	−0.31	+0.11
Social	ADHD→Aut.	+0.44	−0.02
	Aut.→ADHD	−0.47	+0.02
time	ADHD→Aut.	−0.70	−0.15
	Aut.→ADHD	+0.43	−0.00

Note directional opposition for Authentic and Clout in the Aut.→ADHD condition.

Table 9: Average timeline distances (days).

Dataset	First→Dx	Dx→End	First→End
ADHD in ADHD	124 (302)	568 (622)	692 (691)
ADHD in Autism	52 (167)	411 (467)	464 (513)
Autism in ADHD	304 (501)	265 (409)	569 (637)
Autism in Autism	236 (386)	378 (458)	614 (576)

Dx = diagnosis disclosure. Parentheses = SD.

Why these analyses matter. If both tests come back clean, cross-posters do not differ at baseline, and effects survive topic matching, the accommodation interpretation is substantially strengthened. If either reveals a confound, it narrows the scope of the claim but does not eliminate it: the mirror-image directionality across eight categories remains difficult to explain by selection or topic alone.

F Statistical Methodology and Dataset Details

LIWC-22 categories. LIWC-22 (Boyd et al., 2022) produces 115 categories in four tiers: 4 *summary variables* (Analytic, Clout, Authentic, Tone, composite scores relatively robust to topic variation), ∼25 *linguistic dimensions* (function words, pronouns, verb tense), ∼50 *psychological processes* (affect, cognition, social processes), and ∼36 *personal concerns* (work, health, leisure). We tested all 115 per experiment without *a priori* selection, relying on FDR correction to control for multiplicity. The summary variables are particularly important for our accommodation argument because they capture broad stylistic dimensions that are less susceptible to topic confounds than content-specific categories like HEALTH or WORK.

User-level aggregation. For each user u with posts $\{p_1, \ldots, p_n\}$ in a given condition and LIWC category c, we compute a single per-user mean:

$$\bar{x}_{u,c} = \frac{1}{n} \sum_{i=1}^{n} \text{LIWC}(p_i, c)$$

Users with fewer than 3 posts in a condition were excluded to ensure stable estimates. This aggregation is critical: without it, prolific users would dominate the analysis, and pseudoreplication would inflate statistical significance.

Statistical testing. Welch's t-test (unequal variances assumed) with effect size $d = (\bar{x}_1 - \bar{x}_2)/s_p$, where s_p is the pooled SD. For E3 paired comparisons, we use the SD of within-user difference scores. All 95% CIs for d are computed via the noncentral t-distribution with noncentrality parameter $\lambda = d \cdot \sqrt{n_1 n_2/(n_1 + n_2)}$ (independent groups) or $\lambda = d \cdot \sqrt{n}$ (paired). FDR correction follows Benjamini and Hochberg (1995) at $q = 0.05$ across $m = 115$ tests per experiment.

Diagnosis timestamps. For E3, we used the timestamp of each user's first public diagnosis disclosure from the Mindset dataset (Mankarious et al., 2025). Users were included only if they had ≥ 3

Dataset	Users	Posts	Avg Words	Std	Subreddit	Comments	Submissions
ADHD in ADHD	7,758	199,020	85.94	112.21	r/ADHD	171,028	27,992
ADHD in Autism	788	12,621	70.96	113.82	r/autism	11,245	1,376
Autism in Autism	5,706	276,159	64.93	98.54	r/autism	248,597	27,562
Autism in ADHD	2,305	38,470	84.01	108.22	r/ADHD	31,947	6,523

Table 10: Descriptive statistics for cross-posting datasets. Users are non-overlapping between ADHD and autism diagnostic groups.

Table 11: Glossary of LIWC categories featured in this paper's figures and tables. Scores are word-frequency rates, not measures of intent. † marks LIWC *summary variables* (composite scores designed to be relatively topic-independent). See Appendix H for extended interpretation.

Category	One-line definition
AUTHENTIC†	Spontaneous, self-revealing style (more first-person singular, fewer hedges). A stylistic marker, *not* a measure of honesty.
CLOUT†	Confident, authoritative stance (more *we*/*you*, fewer *I*). Reflects relative social standing in the text, not actual influence.
SOCIAL	Rate of words referring to people and social processes. Captures *writing about* social matters, not real-world social engagement.
SOCREFS	Social referents: references to other people (e.g., *they*, *you*, names). Mentions of others in text, not actual interaction.
TIME	Words about time and temporal orientation (e.g., *when*, *soon*, *hour*).
ACHIEVE	Achievement and goal-striving words (e.g., *win*, *success*, *better*).
WORK	Work and occupation words (e.g., *job*, *boss*, *deadline*).
I	First-person singular pronouns (*I*, *me*, *my*); self-focus.
THEY	Third-person plural pronouns (*they*, *them*); reference to other groups.
HEALTH	Health, illness, and symptom words (e.g., *clinic*, *meds*, *pain*).
SUBSTANCES	Substance-related words (e.g., *alcohol*, *caffeine*, medication).
ACQUIRE	Acquiring or obtaining words (e.g., *get*, *find*, *take*).
LIFESTYLE	Personal-life domains, including work, leisure, home, and money.

posts in both pre- and post-disclosure periods. Median pre-disclosure posting span $\approx$ 14 months; post-disclosure $\approx$ 18 months.

Data pipeline. Starting from Mindset's user identifiers and diagnostic labels: (1) re-fetch each user's complete Reddit history via Pushshift (Mindset's original posts are filtered to exclude mental health content), (2) retain only posts in r/ADHD and r/autism, (3) verify zero user overlap between diagnostic groups, (4) remove deleted posts and posts with $<$ 5 tokens, (5) run LIWC-22 and aggregate to user-level means. Final corpus spans 2015–2024 (majority 2019–2023).

Descriptive statistics. Table 10 reports per-subset user, post, and word counts for the four cross-posting datasets.

G LIWC Category Glossary

Table 11 defines every LIWC category featured in this paper's figures and tables. The four categories whose technical meaning most diverges from everyday usage are reproduced in the main text (Table 1).

H LIWC Summary Variable Interpretation

Three LIWC summary variables are central to our analysis. AUTHENTIC (d=0.59, ADHD higher) captures spontaneous, self-disclosing language. CLOUT (d=$-$0.41, autism higher) captures confident, authoritative language. SOCIAL (d=$-$0.52, autism higher) captures references to people and interpersonal interactions. Unlike content-specific categories, these are composite scores designed to be relatively topic-independent, making their strong accommodation effects in E2 harder to explain as purely topical artifacts.

It is worth noting that LIWC scores reflect word-level frequency patterns, not communicative intent. A high SOCIAL score in the autism community does not mean autistic users are more socially engaged, it means they *talk about* social topics more frequently, which is consistent with the community's focus on navigating social difficulties. Similarly, high AUTHENTIC in the ADHD community reflects a linguistic pattern (more first-person pronouns, less formal hedging) rather than a judgment about honesty. These distinctions matter for interpreting the accommodation results: when ADHD users decrease in AUTHENTIC while posting in r/autism, this reflects a shift toward more guarded, formal language, not a decrease in sincerity.

A broader limitation of LIWC is that it operates at the word level and cannot capture syntactic structure, pragmatic function, or discourse-level phenomena. For example, LIWC cannot distinguish between a user who asks many questions (a possible sign of deference to the host community) and one who uses question marks in rhetorical statements. Future work could complement LIWC with dependency parsing to measure syntactic complexity, sentence embeddings to compute stylistic similarity in continuous space, or discourse-level features such as hedge frequency and turn-taking patterns. These approaches would test whether the accommodation patterns we observe at the lexical level extend to deeper structural dimensions of language use.

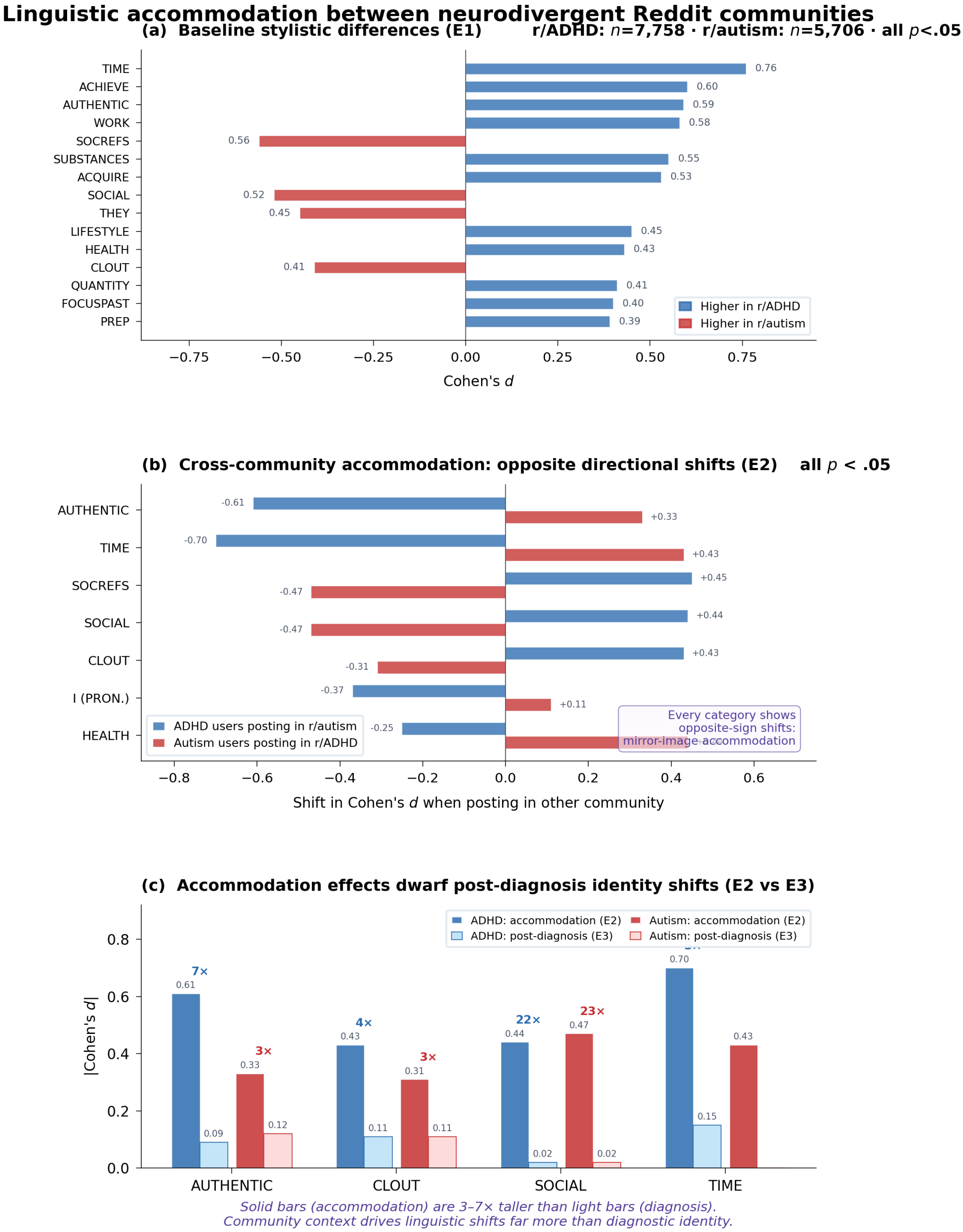

Figure 2: (a) Baseline differences (E1). (b) Cross-community accommodation (E2): mirror-imaged shifts across every category. (c) E2 vs. E3: accommodation (solid) is 3–23× larger than post-diagnosis changes (light).