TOWARD COMPUTATIONAL MEASURES OF SOCIAL COGNITION IN PATIENTS WITH SCHIZOPHRENIA SPECTRUM DISORDERS

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Abstract

Computational methods are increasingly being explored to detect language markers of schizophrenia spectrum disorders (SSD). Despite the importance of social cognition in diagnosis and functional outcomes in this clinical population, it remains underexamined in computational language analysis. This exploratory study applies machine methods from natural language processing and computational linguistics to transcribed speech from patients with SSD and healthy controls to determine whether they are capable of extracting and analyzing linguistic features of social cognition in text samples. We evaluated linguistic features from three categories related to social cognition: perspective taking, emotion processing, and linguistic complexity. In addition, we explored various implementations of these methods, e.g. grouping them together and contextualizing them, which might point to additional ways of quantifying social cognition that could be integrated into future computational text analyses. Patients exhibited increased first-person pronoun use, reduced relative third-person pronoun use, lower modal verb frequency, and decreased linguistic complexity. Emotional content distributions also differed between groups and varied depending on pronoun context, with notable contrasts in the emotional content of speech containing third-person pronouns versus pronoun-absent speech. Our results demonstrate that computational methods can effectively identify relevant linguistic features of social cognition in text. This work establishes a basis to continue to refine computational methods to assess social cognition in SSD that will ultimately advance objective, rapid, and scalable approaches for personalized diagnosis and treatment.

Résumé

Les méthodes informatiques sont de plus en plus explorées pour détecter les marqueurs linguistiques des troubles du spectre de la schizophrénie (TSS). Malgré l'importance de la cognition sociale dans le diagnostic et les résultats fonctionnels dans cette population clinique, elle reste sous-examinée dans l'analyse computationnelle du langage. Cette étude exploratoire applique des méthodes automatiques de traitement du langage naturel et de linguistique informatique à la transcription de la parole de patients atteints de TSS et de témoins sains afin de déterminer si elles sont capables d'extraire et d'analyser les caractéristiques linguistiques de la cognition sociale dans des échantillons de texte. Nous avons étudié les caractéristiques linguistiques de trois catégories liées à la cognition sociale : la prise de perspective, le traitement des émotions et la complexité linguistique. En outre, nous explorons diverses mises en œuvre de ces méthodes, par exemple en les regroupant et en les contextualisant, ce qui pourrait indiquer des moyens supplémentaires de quantifier la cognition sociale qui pourraient être intégrés dans de futures analyses computationnelles de textes. Les patients utilisaient davantage les pronoms de la première personne, et relativement moins les pronoms de la troisième personne, la fréquence des verbes modaux et la complexité linguistique. La distribution du contenu émotionnel diffère également entre les groupes et varie en fonction du contexte pronominal, avec des contrastes notables dans le contenu émotionnel du discours contenant des pronoms de la troisième personne par rapport au discours sans pronom. Nos résultats démontrent que les méthodes informatiques peuvent identifier efficacement les caractéristiques linguistiques pertinentes de la cognition sociale dans un texte. Ce travail constitue une base pour continuer à affiner les méthodes informatiques d'évaluation de la cognition sociale dans les TSS, ce qui

permettra à terme de faire progresser les approches objectives, rapides et évolutives en matière de diagnostic et de traitement personnalisés.

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Contribution of Author

I confirm that I am the sole author of this thesis. I acknowledge the contribution of my supervisor, Dr. Ian Gold, in providing feedback and revisions for this thesis.

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Introduction and Statement of Problem

Language serves as a powerful conduit, translating internal experiences into external expression. It offers a passageway into the intricate cognitive framework and emotional states that shape an individual's life. The nuances embedded within one's language—be it the structure, content, or tone—mirror thoughts, beliefs, and perceptions, and unveil the complexity of the processes shaping a person's reality. This close connection between language and cognition has long been used by the fields of psychiatry and psychology to aid the understanding, diagnosis, and treatment of psychological symptoms. Language analysis has thus profoundly transformed our understanding of the psyche and our ability to treat it.

Language is particularly relevant in the evaluation of psychotic disorders, such as schizophrenia, where negative symptoms include direct disturbances to language production, such as poverty of speech and disorganized discourse (Andreasen & Flaum, 1991). Traditionally, practitioners have harnessed the potential of language through diagnostic interviews, psychological assessments, and therapeutic interactions. However, traditional methods have their limitations. The descriptive power of clinical tests can be limited by incomplete response sets when patients and participants don't participate in follow-up (Corcoran et al., 2020). In addition, they often consist of ordinal scales that are insufficiently precise to capture the nuances of the traits they aim to describe. For example, scoring a trait on a scale from 1-10 may fail to capture subtle differences between individuals who fall within the same category. This might be overcome using manual linguistic analyses using qualitative data, but conducting studies with this approach is expensive with respect to time, effort, and money making it difficult to leverage the full power of manual evaluation on a large scale. Finally, expert opinion risks subjectivity, and these judgments can lose comparability across the wider population (Corcoran, Mittal, Bearden, E. Gur, et al., 2020).

Recently, computational methods in language analysis, such as natural language processing (NLP), have gained traction. Applied to the field of psychiatry, they offer a means to overcome the constraints of traditional clinical tools and take advantage of the rich assortment of clinically relevant features that language has to offer. Machine approaches are capable of more fine-grained feature evaluation and with a fraction of the time and money it would cost for a clinician to manually complete the task. Furthermore, while traditional evaluation methods often require participants to complete an entire response set or follow up on multiple testing days to obtain a full score, computational speech and text analysis can be applied to any available language sample, allowing for assessment without relying on complete responses or risking data loss when follow-up is incomplete. Once these tools demonstrate reliability and validity, they will offer an objective method for evaluating psychiatric symptoms, thereby helping to enhance the comparability of findings across independent studies that often struggle with inconsistencies due to subjective or diverse assessment methods. In these ways, computational linguistic measures promise a more practical way to harness the power of language to understand cognitive and emotional states.

NLP is already being used to evaluate populations with psychotic illnesses, such as schizophrenia, schizoaffective, and schizophreniform disorder, for a variety of different applications. Hernández et al. (2023) outline both *descriptive* roles of NLP markers, such as screening patients or predicting future outcomes, and *mechanistic* roles, such as indicating pathological mechanisms at the cellular, physiological, and systems levels (Hernández et al., 2023). Current research aims to identify NLP markers that can establish a clinical diagnosis, detect symptoms more accurately and quickly, predict the onset of future symptoms and the course of the illness, and stratify patient symptoms for more targeted care (Belouali et al., 2021; Birnbaum et al., 2019, 2020; Corona Hernández et al., 2023; Huang et al., 2020; Mundt et al., 2012a; Ni et al., 2020; Silva et al., 2023; Stanislawski et al., 2021).

The literature on machine methods for investigating psychotic disorders is already wide and varied (Alonso-Sánchez et al., 2022; Belouali et al., 2021; Bilgrami et al., 2022; Birnbaum et al., 2019, 2020; Boyd & Schwartz, 2021; Corcoran et al., 2018; Corcoran, Mittal, Bearden, E. Gur, et al., 2020; Corona Hernández et al., 2023; Foltz et al., 2016; Girard et al., 2022; Hitczenko et al., 2021; Huang et al., 2020; Ku et al., 2021; Mundt et al., 2012; Ni et al., 2020; Ratana et al., 2019; Silva et al., 2023; Stanislawski et al., 2021; Tang et al., 2023). Nonetheless, this work is still in its infancy and more studies with larger and more diverse samples are needed (Foltz et al., 2016). Moreover, much of the work to date has focused on *language abnormalities* in psychosis, such as poverty of content, reduced syntactic and grammatical complexity, and disorganized, vague, or off-topic discourse (Alonso-Sánchez et al., 2022b; Bilgrami et al., 2022; Boyd & Schwartz, 2021; Corcoran et al., 2018; Corcoran, Mittal, Bearden, E. Gur, et al., 2020; Foltz et al., 2016; Girard et al., 2022; Hitczenko et al., 2021; Ku et al., 2021; Ratana et al., 2019; Tang et al., 2023). While these are critical characteristics, they can only partially account for symptomology on their own. Other symptoms, such as those related to *impairments in social cognition*, are typically assessed using traditional measures, yet the potential of machine-based methods for evaluating these social-cognitive symptoms remains largely unexplored.

Another lacuna in the literature is the use of machine methods to investigate *social cognition* in psychosis. Impairments in social cognition are central to the phenomenology of psychosis and play a critical role in the diagnosis and treatment outcomes for affected individuals

(Biedermann et al., 2012; Billeke & Aboitiz, 2013; Bora et al., 2009; Dimopoulou et al., 2017; Gavilán Ibáñez & García-Albea Ristol, 2013; Healey et al., 2016; Javed & Charles, 2018; Mondragón-Maya et al., 2017; S. Vyas et al., 2017). However, there are few studies to date that look at the potential for machine methods to identify relevant features of social cognition in language. **The aim of the present study, therefore, is to identify features of social cognition in text using computational methods that are capable of distinguishing patients with psychotic disorders from healthy controls.** A method fit for purpose would identify a set of features of social cognition in transcribed discourse. These features, in turn, would help to provide a more fine-grained understanding of *which aspects* of social cognition are most affected in this population and how they differ from healthy individuals. This might ultimately prove useful in stratifying patients for more targeted treatment of symptoms and for increasing the success of algorithms designed for diagnosis, prevention, and predictive modeling of illness trajectories.

Rationale

Computational methods of language analysis have proven powerful in detecting features in text that are relevant to psychiatric conditions (Belouali et al., 2021; Birnbaum et al., 2020; Hernández et al., 2023.; Javed & Charles, 2018; Mundt et al., 2012; Ni et al., 2020; Silva et al., 2023a; Stanislawski et al., 2021). These methods are capable of overcoming the limitations of traditional methods of evaluation, which are effortful, costly, risk subjectivity, and lack precision (Corcoran, Mittal, Bearden, E. Gur, et al., 2020). Existing studies using computational linguistic measures have primarily explored language-specific cognitive impairments related to schizophrenia symptoms, such as those related to syntactic complexity and semantic coherence, but *they have largely overlooked deficits in social cognition* (Alonso-Sánchez et al., 2022a; Bilgrami et al., 2022; Boyd & Schwartz, 2021; Corcoran et al., 2018; Corcoran, Mittal, Bearden, E. Gur, et al., 2020; Foltz et al., 2016; Girard et al., 2022; Hitczenko et al., 2021; Ku et al., 2021; Ratana et al., 2019; Tang et al., 2023).

Objective

The objective of the current study is to address the gap in computational research focusing on linguistic features associated with social cognition in patients with psychotic disorders. Following this objective, the **primary aim of this investigation is to identify features of social cognition in text using computational methods that are capable of distinguishing patients with psychotic disorders from healthy controls.** To achieve this aim, the present investigation is an **exploratory study of computational methods** capable of extracting and analyzing linguistic features related to social cognition from text samples. In addition, we explore **various implementations of these methods,** e.g. grouping them together and contextualizing them, which might point to additional ways of quantifying social cognition that could be integrated into future computational text analyses.

Specific Aims

The project has two specific aims. First, we aim to identify linguistic features of social cognition that can be reliably detected in our text samples. Namely, we seek features of language that fall under three categories related to social cognition: perspective taking and mentalization, emotion processing, and linguistic complexity. Second, we aim to investigate whether these features can be quantified using computational methods from the fields of natural language processing and computational linguistics.

Literature Review

Clinical Population

Psychotic disorders, particularly schizophrenia, are of paramount importance in the field of mental health and clinical research. Schizophrenia is a complex and debilitating mental illness characterized by a range of symptoms, including hallucinations, delusions, disorganized thought and speech, and impaired social functioning (Andreasen & Flaum, 1991). The prevalence of psychotic illnesses is significant, affecting approximately 4% of the Canadian population with onset typically occurring in late adolescence or early adulthood (Lecomte et al., 2022). This disorder not only causes disability and immense distress in individuals affected but also imposes a substantial burden on families, communities, and healthcare systems (Goeree et al., 2005; Hor & Taylor, 2010; Lecomte et al., 2021). Furthermore, schizophrenia is associated with an increased risk of comorbid conditions such as substance abuse, depression, and anxiety disorders, further complicating its management and treatment (Buckley et al., 2009).Therefore, studying psychotic disorders like schizophrenia is crucial for advancing our understanding of their etiology, risk factors, neurobiological mechanisms, and effective interventions. Such research contributes to improving diagnostic accuracy and treatment outcomes and promoting better support and care for individuals living with these challenging conditions (Corrigan & Watson, 2002).

Social Cognition in Psychotic Disorders

Social cognition, in particular, is crucial to the study of psychotic disorders for several reasons. Individuals with psychotic disorders exhibit significant impairments in social cognition, which account for a substantial portion of the challenges encountered in daily functioning (Biedermann et al., 2012; Billeke & Aboitiz, 2013; Bora et al., 2009; Dimopoulou et al., 2017; Gavilán Ibáñez & García-Albea Ristol, 2013; Healey et al., 2016; Javed & Charles, 2018; Mondragón-Maya et al., 2017; S. Vyas et al., 2017). Indeed, Theory of Mind (ToM)—the ability to understand the beliefs, desires, intentions, and perspectives of other people, and a key component of social cognition—is the strongest predictor of functional outcomes in psychosis (Fett et al., 2011). Understanding these social-cognitive deficits is thus essential for developing targeted interventions to improve social interactions and quality of life for patients (Green et al., 2015).

Importantly, the term *social cognition* does not just refer to a single process, but rather a diverse set of multimodal processes that work together to create a representation of minds and emotions outside of our own and enable us to navigate the social world. Its multiple sub-modalities include emotion processing, ToM, attributional style, social knowledge, and social perception (Green et al., 2005, 2008; Kee et al., 2009; Pinkham et al., 2018). As such, to understand the nature of social impairments in a population requires a comprehensive study of each of these sub-processes and, more significantly, how they interact. Individuals with schizophrenia spectrum disorders (SSD) as well as those at clinical and familial high risk for psychosis, robustly demonstrate limitations in all of the abovementioned subcomponents of social cognition (Green et al., 2012; Kohler et al., 2014; Oliver et al., 2021; Tang et al., 2017). Studying the nuances of social processing in patients can help differentiate between different subtypes of psychotic disorders and aid in more accurate diagnosis and personalized treatment plans (Mueser et al., 2006). Additionally, determining exactly *which* of these social processes are affected in patients with psychotic disorders and *how* each of them manifest can provide clues to the neural mechanisms underlying them. In this way, deconstructing social cognition in psychotic illnesses may not only have clinical outcomes, but lead to advances in neurobiological models of these conditions as well. It is therefore important to develop methods of evaluation that can target more discrete features of social cognition for analysis. Overall, advancing our knowledge of social cognition in psychotic disorders is integral to improving clinical outcomes, enhancing our understanding of these complex disorders at both the behavioral and neural levels, and developing more effective interventions.

Further, since social cognition is multifaceted, tests for social perception and behaviors are equally varied in what they measure (Schaafsma et al., 2015). This can make it difficult to compare results from independent studies and reach conclusions about the mental processes driving social cognition. For example, consider two tests that are commonly used to assess ToM: the Reading the Mind in the Eyes Task (RMET) (Baron-Cohen et al., 1997) and the False Belief Task (FBT) (Baron-Cohen et al., 1985). In the RMET, participants are shown photos of the eye region of a face. The participant must then choose one term from a group of mental state words that best matches the expression in the eyes. The FBT asks subjects to follow a storyline that might come in various formats, such as a picture story board, a short video, or even a written script. The participant is then asked to demonstrate ToM by recognizing that a character in the story holds a belief that differs from reality. The RMET is likely to engage various mental processes related to mental state perception and attribution, whether specifically tied to visual and facial stimuli or not. In contrast, the FBT focuses more on the attribution of belief rather than mental state recognition and may involve visual scene interpretation or linguistic processing. Yet, they are both considered measures of ToM. On the one hand, it is of course important to explore social cognition as it presents itself in multiple cognitive modalities. On the other hand, in order to ask where impairments and individual differences in social cognition occur, we need measures of social cognition that are capable of testing multiple components of social cognition while controlling for the mental processes that are demanded by the task. Language analysis can contribute to addressing this concern. Many components of social cognition, such as perspective taking, emotion recognition and attribution, belief information, and intentionality are manifested by linguistic expression. Therefore, analyzing social-cognitive features in language allows us to directly compare how these subprocesses are present and utilized while controlling for the influence of other mental processes required by different task formats.

Language and Social Cognition in Psychotic Disorders

Speech disturbances are also characteristic of SSD and include disorganized speech, such as derailment, tangentiality, and incoherence, and poverty of speech (Kircher et al., 2018; Lim et al., 2020; Parola et al., 2023; Tan et al., 2014) and they have also been observed in clinical and familial at-risk individuals (Corcoran et al., 2018; Morgan et al., 2017; Solot et al., 2020). Traditionally, these speech disturbances have been viewed as a reflection of formal thought disorder (FTD) (Kircher et al., 2018; Tan et al., 2014; Tang et al., 2023). However, it has been found that while around 80% of individuals with schizophrenia exhibit speech disturbances, only about 20% of this population meet the diagnostic criteria for FTD (Tan et al., 2014). Alternatively, many posit that language disturbances arise instead from deficits in social-cognitive functioning (Brown & Kuperberg, 2015; Palaniyappan et al., 2019; Palaniyappan &

Venkatasubramanian, 2022; Silva et al., 2023; Vasil et al., 2020). This research suggests that disturbances to social cognition and speech in patients with schizophrenia spectrum disorders (SSD) might not be *distinct outcomes* of the condition but are rather *interconnected* with one another (Palaniyappan et al., 2019; Wible, 2012). This potential connection further underscores the importance of studying social cognition through linguistic output in this population.

The Bayesian active inference model (Palaniyappan & Venkatasubramanian, 2022; Silva et al., 2023; Vasil et al., 2020) links speech disturbances in psychosis to deficits in social cognition. In this model, the speaker receives important signals from the person they are speaking to. If a discrepancy is detected between the information they receive from the listener and what was predicted, the speaker must revise the Bayesian "prior," which is the representation of the intended communication. For example, if the speaker notices that the listener seems to not be understanding what is being communicated, the speaker can add additional information or restate the information in a different manner. The speaker is using active feedback to adjust their discourse to the listener. When the speaker's priors are imprecise, they update their model too frequently, which results in empty or disorganized speech (Brown & Kuperberg, 2015; Palaniyappan & Venkatasubramanian, 2022; Silva et al., 2023; Vasil et al., 2020). If this model proves to be true, studying how social cognition presents itself *specifically* in the language of individuals in this clinical population is of particular interest.

Harnessing Language to Understand Psychiatric Disorders

Because the content and structure of language reflect the nuances of thoughts, emotions, and their contexts in its portrayal of internal human experiences, studying discourse directly allows us to leverage language for gaining insight into psychiatric disorders. Psychologists and psychiatrists have long relied on aspects of language for the diagnosis and treatment of their patients as well as to aid scientific investigation of psychiatric disorders (Corcoran, Mittal, Bearden, Gur, et al., 2020). However, traditional methods for evaluating psychiatric disorders rely on expert opinion, which is both costly on a large scale with respect to effort, time, and money and risks subjectivity and inadequate inter-rater reliability (Corcoran, Mittal, Bearden, E. Gur, et al., 2020). Furthermore, many clinical ratings rely on ordinal scales which are not precise. Recently, computational methods have provided new tools for analyzing language in psychiatric populations. They offer possible solutions to many of the challenges faced by traditional methods of language evaluation.

Computational Methods for Language Analysis in Psychiatric Disorders

Computational approaches to language analysis, such as natural language processing (NLP) and computational linguistics, have become a popular way of leveraging the full potential of language by offering a more objective and efficient evaluation of psychiatric disorders (Corona Hernández et al., 2023). These methods excel at examining discrete and nuanced features of language in order to provide a more detailed description of the mental states it expresses.

Computational methods are already being applied to the problem of language interpretation in psychotic illnesses. The approaches and outcomes are wide and varied. Some applications include the detection of diagnoses, symptoms, and warning signs for clinical high-risk individuals, monitoring the effects of treatment, and predicting illness onset, course, and potential relapse (Belouali et al., 2021; Birnbaum et al., 2020; Corona Hernández et al., 2023; Huang et al., 2020a; Mundt et al., 2012; Ni et al., 2020; Silva et al., 2023; Stanislawski et al., 2021). All of these applications can help to create more targeted and timely treatments. Many of the studies to date have focused on differences in features of language-specific cognition in schizophrenia, such as syntactic complexity, semantic coherence, and impoverished discourse (Alonso-Sánchez et al., 2022; Bilgrami et al., 2022; Boyd & Schwartz, 2021; Corcoran, Mittal, Bearden, Gur, et al., 2020; Foltz et al., 2016; Girard et al., 2022; Hitczenko et al., 2021; Ku et al., 2021; Ratana et al., 2019; Tang et al., 2023). While this literature is both exciting and promising, it leans heavily toward this subset of linguistic features. As mentioned, deficits in social cognition are also key features for diagnosing and treating psychotic disorders (Fett et al., 2011; Green et al., 2008, 2015; Pinkham et al., 2018). However, to date, few computational studies have looked at features of social cognition in the language of patients.

Computational Methods of Language Analysis for Social Cognition

To our knowledge, very few computational studies have yet tried to extract *social* cognitive features from text, and even fewer have considered these social features in the context of psychiatric illnesses. Lee et al. (2021), used human raters to label phrases in text on a scale of 0-3 corresponding to the level of ToM present in the utterance. The levels were based on the extent to which the sentence was "other-focused" in representing mental states (Lee et al., 2021). Subsequently, they explored various NLP models to determine which could best identify ToM in the text, and they found that different classifiers were better at predicting different levels of ToM. Mascio et al. (2021) aimed to derive multiple cognition scores, including social cognition, from text of patients with schizophrenia using an NLP model (Mascio et al., 2021). Like Lee and colleagues, their work relied on the manual labeling of sentences by human raters. For computational language models to eventually overcome the need for independent, manual language evaluation and labeling, we must identify which features can be reliably detected in text using computational methods. In the present study, we use a dataset that is not yet accompanied by clinical ratings. So, rather than measuring the relationship between our computationally extracted features and social cognition, we compare these features in the clinical and healthy populations. We focus heavily on the *exploration of social feature identification* and extraction from text in these two populations.

A study by Tang et al. (2023) compared clinical ratings with linguistic features of social cognition in patients with schizophrenia spectrum disorders. They used five different computational strategies to extract these features from text and determined how they correlated with clinical scores of emotion processing, mentalization, and attribution bias (Tang et al., 2023). These clinical scores were based on manual ratings and some non-linguistic measures of social cognition. We expand upon this work here by aiming to find computational methods that can reliably extract linguistic markers of emotion and mental state processing. In line with this aim, the present investigation asks (1) if linguistic features of social cognition be reliably detected in our text samples, and (2) if these features can be quantified using computational methods.

Linguistic Features of Social Cognition and Their Detection Using Computational Methods

In the current investigation, we focused on a subset of three fundamental functions of social cognition that are also of particular importance to the population of people with psychotic disorders: perspective taking and mentalization, emotion processing, and linguistic complexity (Eack et al., 2017; Larøi et al., 2010; Schiffman et al., 2004; St-Hilaire et al., 2008; Tang et al., 2021, 2023). Following our first specific aim, we determined whether we could identify features of language that measure each of these three functions social cognition and that can be reliably detected in our text samples. With respect to the second specific aim, which is investigate whether these features can be quantified using computational methods from the fields of natural language processing and computational linguistics, we explored various computational methodologies and their implementations. We determined whether the computational methods selected for these analyses were capable of detecting a distinction in the presentation of these features between patients with psychotic disorders and healthy controls.

Perspective Taking and Mentalization

Critical to successful ToM, a core component of social cognition, is the ability to take the perspective of another person with respect to their emotions, thoughts, or beliefs (Bradford et al., 2015; Selman, 1975). For this reason, perspective taking has been studied in patients with psychotic illnesses, and many researchers have found specific impairments in perspective taking when considering it in isolation as a sub-function of social cognition (Eack et al., 2017; Schiffman et al., 2004; Tang et al., 2021, 2023). The use of first- and third-person pronouns has been taken by many researchers to be a measure of perspective taking because pronouns reflect how individuals position themselves and consider others in social interactions (Brunyé et al., 2009; Hartung et al., 2016; Ricard et al., 1999; Smyth, 1995). Higher usage of first-person pronouns (e.g., "I," "me") may indicate a self-focused perspective, whereas third-person pronouns (e.g., "he," "she," "they") suggest consideration of others' perspectives. We have incorporated these measures in the current study following results from other investigations that have found differences in first- and third-person pronoun use in patients with psychotic disorders compared to healthy controls. Findings on pronoun use in individuals with SSD largely indicate an overuse of first-person pronouns (Bersudsky et al., 2005; M. Chaves et al., 2020; M. F.

Chaves et al., 2023; Cheek & Anthony, 1970; Lundin et al., 2023; Strous et al., 2009; Zomick et al., 2019) and of first person *singular* ("I") pronouns in particular (Buck & Penn, 2015; Chan et al., 2023; Lundin et al., 2023; Tang et al., 2021, 2023; Zomick et al., 2019). The results for third-person pronouns are somewhat mixed, with some reporting no group differences between patients with psychotic disorders and healthy controls (Buck & Penn, 2015; Lundin et al., 2023). However, a clearer interpretation emerges when considering *third-person plural* and *singular* pronouns separately, with many authors typically reporting higher third-person plural and lower third-person singular pronoun use in patients with schizophrenia (Bae et al., 2021; M. F. Chaves et al., 2023; Fineberg et al., 2015; Strous et al., 2009). Additionally, much work has indicated higher use of null third-person pronouns—those that lack a clear referent—in the clinical population (Buck & Penn, 2015; M. Chaves et al., 2020; Strous et al., 2009). Similarly, mentalization—the ability to infer and reflect on others' mental states—is often examined through linguistic markers, including verb use. A number of investigators have explored the use of modal auxiliary verbs (e.g., "could," "should," "might") which are thought to indicate conditional reasoning, uncertainty, or intentions, which are essential to mentalizing (Moon, 2016; Guo, 1994; Tang et al., 2023). Previous research has found that these verb forms consistently show up as prominent markers of psychotic disorders (Strous et al., 2009). In the present study, we examine first- and third- person pronoun use alongside verb use to expand upon these findings and determine whether they can be replicated using machine methods. To address our second scientific aim, which is to investigate whether there are machine methods that are capable of reliably measuring our features of interest, we quantified parts of speech using the NLTK POS parser (Bird et al., 2009).

Emotion Processing

Emotion processing is another critical component of social cognition and interpersonal functioning which is often affected in individuals with psychotic disorders. Deficits in recognizing, interpreting, and responding to emotional cues contribute to difficulties in forming and maintaining social relationships, exacerbate clinical symptoms, and impair overall quality of life (Larøi et al., 2010; St-Hilaire et al., 2008). Studying emotion processing in this population is therefore essential for understanding the underlying mechanisms of social dysfunction and for developing targeted interventions. Several studies have explored emotion processing in psychotic populations using various methods. For instance, facial emotion recognition tasks have been widely employed to identify deficits in recognizing emotional expressions (Gao et al., 2021; Larøi et al., 2010; Martin et al., 2020) as have various other multimodal and multisensory behavioral measures of emotion processing (Buck & Penn, 2015; Flechsenhar et al., 2022; Gil-Sanz et al., 2004; Kohls et al., 2020; Lin et al., 2018; Tang et al., 2021; Taylor et al., 2012). In studies that measure emotion in language, sentiment analysis and emotion classification algorithms have been used to quantify emotional valence and intensity in patients' speech or written narratives (Gutiérrez et al., 2017; Tang et al., 2021). Taken together, this body of research consistently shows that individuals with psychotic disorders display an increased tendency to linguistically express negative emotions (Buck & Penn, 2015; Cho et al., 2017; Corcoran & Cecchi, 2020; Gao et al., 2021; Lyons et al., 2018; Zomick et al., 2019). The expression or perception of anger, fear, and sadness in particular (Bae et al., 2021; Minor et al., 2015) has been found to have a relationship with other factors such as distress (Lyons et al., 2018).

Some investigators, such as Cohen et al. (2009), have even observed this increase in negative word use in relation to *positive* events. Another frequent finding is that patients tend to exhibit aberrant arousal—specifically, over-arousal—in response to neutral or negative stimuli (Comparelli et al., 2020; Llerena et al., 2012). Of particular interest for the current study, emotional over-arousal has also been observed in neutral *social settings,* and it has been suggested that this over-arousal leads to a misplaced cognitive bias in social settings which leads to poor social functioning (Haralanova et al., 2012). Other investigations support an association between this impaired emotional regulation and functional social outcomes in patients. For example, in the context of social cognition some investigations have found the increase in negative emotion words to be correlated with poorer ToM and greater hostile or aggressive attributional style (Bae et al., 2021; Buck & Penn, 2015). In particular, Buck & Penn (2015) found that *first-person* pronoun use was associated with impaired ToM and an increase in hostile or aggressive attribution bias. In the present study, we analyze the language of patients and controls using an emotion recognition algorithm in an attempt to replicate these findings using an automatic, state-of-the-art language model for emotion recognition (Savani, n.d.). If successful, automatic methods offer a robust and scalable measure of emotion processing. Importantly, Gao et al. (2021) points out that since so many studies have shown that patients demonstrate an increase in negative emotion words, many studies have begun to study negative emotion exclusively. They advocate that investigators continue to study *all six* basic emotions to obtain more balanced data. Our emotion recognition algorithm does just that by incorporating sadness, love, surprise, fear, anger, and joy. To our knowledge, the present study is also the only study to consider emotion word use *within the linguistic context* of other features of social cognition—for example, we investigated whether complexity differs in the context of first- versus third-pronoun use—rather than measure *correlations* between emotional content and other social-cognitive features.

Linguistic Complexity

Linguistic complexity is another key marker of social cognition, reflecting an individual's ability to understand the complex thoughts, emotions, and perspectives of others and communicate their own. It is often quantified in text using measures such as the total amount of speech or the average number of words per sentence, which serve as proxies for syntactic and semantic elaboration (Bedi et al., 2015; Corcoran et al., 2018; Rezaii et al., 2019). These metrics provide insight into a speaker's cognitive abilities, as well as their capacity to engage with subtle social cues adequately. In the present study, we build on these established approaches by quantifying linguistic complexity by means of the total number of phrases, total number of words, and words per sentence *across various contexts*. Novel to our approach is the exploration of complexity in the context of pronoun use, investigating whether linguistic complexity varies depending on the perspective taken by the speaker. To address our second specific aim, which is to identify computational methods for quantifying our selected social features in text, we performed word counts in *subsets of text* generated by part-of-speech (POS) tagging to measure complexity specifically where different parts of speech were being utilized. By examining how complexity interacts with other linguistic features of social cognition, we aim to identify more diverse methods for extracting socially relevant information from text that might arise when we consider the impact of context on our features. Ultimately, our goal is to contribute to computational text analysis techniques that leverage these features to better understand and diagnose social cognitive impairments. We believe that exploring complexity in a variety of contexts could provide valuable insights and help guide the development of future computational analyses.

Methods

Dataset

The present investigation combined participant data from the Thematic Apperception Test (TAT; (Murray, 1943)) from two datasets: the DISCOURSE dataset (Palaniyappan et al., 2022) and the Topsy dataset (Alonso-Sánchez et al., 2022; Dalal et al., 2025). These datasets are available through PsychosisBank, an open database from the Discourse in Psychosis project (Palaniyappan et al., 2022). Combining these two datasets resulted in one set containing a total of 220 participants, of which were 79 healthy controls and 141 were patients. Table 1 details participant demographic information as well as patient statuses and diagnoses.

DISCOURSE Dataset

The DISCOURSE dataset consists of data from 79 total individuals: 39 patients with psychotic disorders and 40 healthy controls. The patients in this dataset fall between first-episode psychosis (FEP) and chronic (3+ years of clinical follow up) status. All patients were medicated at the time of data collection. Of the 39 patients, 25 have been diagnosed with schizophrenia, 6 with schizoaffective disorder, and 8 with psychosis (not otherwise specified) (Table 1). The inclusion criteria for patients were that they were between 18-50 years of age and met the operational criteria for a psychotic disorder (schizophrenia, schizoaffective or schizophreniform illness) according to the Diagnostic and Statistical Manual of Mental Disorders (DSM) 5th edition (American Psychiatric Association, 2013).

Topsy Dataset

The Topsy dataset consists of data from 141 total individuals: 102 patients with psychotic disorders and 39 healthy controls. At the time of data collection, 66 of the 141 patients were identified as first-episode psychosis (FEP), 18 were clinical high risk (CHR), and 18 were chronic (had maintained their status and/or clinical follow up for 3+ years). At a later time point, some of these patients received a diagnosis; 72 were diagnosed with schizophrenia spectrum disorders (SSD), including 63 with schizophrenia, 4 with schizoaffective disorder, 1 with schizophreniform disorder, and 4 with psychosis (not otherwise specified). Patient statuses and diagnoses are outlined in Table 1. The inclusion criteria for patients were that they were between 18-50 years of age and had met the operational criteria for a psychotic disorder (schizophrenia, schizoaffective or schizophreniform illness) according to the DSM 5th Edition (American Psychiatric Association, 2013). FEP participants were acutely psychotic and medication naïve. The CHR participants were not all entirely asymptomatic, though not acutely symptomatic, and they were also unmedicated. All chronic patients were symptomatic and medicated. Patients were followed for over 6 months to determine the validity of a diagnosis of first-episode schizophrenia.

Table 1. Participant Characteristics

Measure	*Dataset*		PT			HC		
			n	MEAN	SD	n	MEAN	SD
Age								
	Combined		122	24.58	6.23	77	24.1	5.1
Education								
	Topsy	# Years of education	67	12.73	1.81	36	14.14	2.18
			n	%		n	%	
Education								
	DISCOURSE	≤ Grade 9	0	0		0	0	
		≤ Grade 12	6	15.38		0	0	
		Highschool	16	41.03		7	17.5	
		College/Vocational	11	28.21		3	7.5	
		BA/BSc	6	15.38		16	40	
		MA/MSc/PhD	0	0		14	35	
		Total	39			40		
Sex								
	Combined	Female	28	22.95		25	32.47	
		Male	94	77.05		52	67.53	
Patient status								
	Topsy	FEP	66	64.71				
		CHR/FHR	18	17.65				
		Chronic (3+ Years)	18	17.65				
Diagnosis								
	Combined	Schizophrenia	88	62.41				
		Schizoaffective	10	7.09				
		Psychosis NOS	12	8.51				
Study total counts								
	Topsy		102			39		
	DISCOURSE		39			40		
	Combined		141			79		
	N=220							

Note 1: the data presented in the current study is based on the combined DISCOURSE and Topsy datasets. Where possible, the numbers reflect the combined sets. Education information reflects each set individually because the available participant characteristics for each set are in different formats. Additionally, patient status is only available for the Topsy dataset. Percentages for each patient status are therefore calculated with respect to the total number of patients in the Topsy dataset only, not the combined dataset. Note 2: study total counts are given at the bottom. Characteristic information was missing for a small subset of participants, so the total n for each characteristic might not sum to the population totals. Note 3: FEP = first-episode psychosis; CHR = clinical high risk; FHR = familial high risk; NOS = not otherwise specified; HC = healthy controls; PT = patients.

Data

Each of the two datasets combined here contains data from the TAT (Murray, 1943). The TAT was chosen because it requires participants to describe what they see in photos containing multiple people engaged in various activities. Therefore, it should engage socially relevant thought processes such as mental and emotional state attribution and intention understanding.

The data is in text format. It contains Otter.ai-transcribed text from participant speech during the TAT. During this task, participants were presented with three photos depicting different scenes, all containing two or more individuals. For each photo, they were asked to elaborate on what they saw during one minute of spontaneous speech. Interviewers provided participants with an instructional prompt such as "I am going to show you some pictures, one at a time. When I put each picture in front of you, I want you to describe the picture to me, as fully as you can. Tell me what you see in the picture, describe what you see in this image, and what you think might be happening." The present analyses are based on the pooled transcribed speech data from all three photos.

Text processing

All transcribed text was originally contained in Microsoft Word documents. The text was parsed and output to individual text files for each participant. Then, the text was filtered so that the interviewer speech was removed and the files contained only participant speech.

Detecting Features of Social Cognition

The features of social cognition being explored here fall into three categories: perspective taking and mentalization, emotional content, and linguistic complexity. To measure perspective taking and mentalization, we looked at pronoun and verb use. We assessed six emotions (love, anger, fear, sadness, surprise, and joy) in the text samples. Complexity measures included words per sentence and number of sentences.

Perspective Taking and Mentalization

We examined various features of perspective-taking and mentalization: first-person pronoun (denoted hereafter as 1PP), third-person pronoun (3PP) and verb use following two studies by Tang and colleagues (Tang et al., 2021, 2023). Additionally, we observed these features in the context of our complexity and emotional content features. Third-person pronouns and verbs were identified and extracted as tokens using the NLTK POS parser (Bird et al., 2009).

Emotional Content

To identify emotional content in text, we used the bert-based-uncased-emotion model by Bhadresh Savani (Savani, n.d.) which was trained on the Dair-AI emotion dataset (DAIR-AI, n.d.). This model classifies text based on six emotions: sadness, joy, love, anger, fear, and surprise and outputs the probabilities of each emotion with a continuous value from 0-1. The model was chosen because it approximates Eckman’s widely studied six basic emotions, with love taking the place of disgust (Ekman, 1999). Moreover, it achieved an accuracy score of 94.05 and an F1 score of 94.06, which was higher than the distilbert-base-uncased-emotion, roberta-base-emotion, and albert-base-V2-emotion models. For these reasons, it was selected as good candidate for identifying emotional content in our text samples. Our features for emotional content are thus the six emotions: love, fear, anger, sadness, joy, and surprise. For each sentence in a file, the emotion probabilities were computed. For each file, the average emotion probabilities across all sentences in the file were computed after normalizing by the number of sentences in the file. We applied this method to two subsets of text for comparison: sentences containing no pronouns (the “non-social” condition) and sentences containing third-person pronouns (the “social” condition)

Linguistic Complexity

In the present study, we are concerned with measures of complexity as a proxy for social cognition following a body of research that attributes loss of speech complexity to impairments in social cognition (Docherty et al., 2013; Harrow M & Quinlan DM, 1985; Rochester & Martin, 1979; Singer & Wynne, 1965). Instead of looking directly at language formation, therefore, we chose methods that could be interpreted in the context of other socially relevant features. Following several investigators we chose to examine the average words per sentence, average total words used, and average total number of sentences for each participant (Bedi et al., 2015; Corcoran et al., 2018; Rezaii et al., 2019). Additionally, we considered the number of words per sentence in various subsets of text for comparison: all sentences, sentences containing a first-person pronoun, those containing a third-person pronoun, and those without any pronouns. In this way, complexity was evaluated both in the text as a whole and in the context of other features of social discourse.

Statistical analyses

None of the features, apart from verb frequency, follow a normal distribution, but most demonstrate comparable variances between populations. A few methods were explored to fit the data to a normal distribution without success. A log transformation is not possible because emotion scores are between 0 and 1. Square root and Box-Cox transformations were also not possible. We therefore used the non-parametric Mann-Whitney U test to compare features between populations. Levene's test was used to assess equality of variances as a pre-condition. Effect sizes are reported using both Cliff's delta and the Rank-Biserial Correlation for all variables except for verb frequency, where it is reported using Cohen's *d*.

Results

Table 2 summarizes the population averages and statistical test results for each variable.

Perspective Taking and Mentalization

The analysis of frequency counts revealed several notable differences between patients and healthy controls. Patients exhibited a significantly higher frequency of first-person pronouns relative to their total word count compared to healthy controls (U = 4093, p = 0.0011). Patients also used a slightly higher frequency of third-person pronouns that was not statistically significant (U = 5085.5, p = 0.2857). Regarding verb use, patients demonstrated a significantly higher frequency of verbs compared to healthy controls (t = -3.022, p = 0.0028). Modal auxiliary verbs were standardized by the total number of verb phrases, and healthy controls showed a higher usage though this difference was not significant (U = 5971, p = 0.3754).

In addition to performing total frequency counts of these parts of speech, we explored their relative frequencies to other parts of speech. Patients had a higher first-person pronoun to third-person pronoun ratio (1pp:3pp). However, this difference was not significant (U = 4896.5, p = 0.1597). Similarly, patients exhibited a lower ratio of modal verbs to total verb phrases (MD:VP), suggesting that relatively few verbs were used to capture intentions, obligations, and states of possibility compared to healthy controls. This difference was also not significant (U = 6363.5, p = 0.0794). Regarding the ratio of third-person pronouns to modal verbs (3pp:MD), patients used fewer modal verbs per third-person pronoun than healthy controls. Again, this difference did not reach statistical significance (U = 16248.5, p = 0.0790). The same trend was observed for the ratio of first-person pronouns to modal verbs (1pp:MD), where patients used fewer modal verbs per first-person pronoun compared to healthy controls, but this difference was not significant (U = 20292.5, p = 0.7945).

In terms of sentence types, patients had a higher ratio of third-person pronoun sentences to no-pronoun sentences (3pp:noPro), suggesting that they used more utterances about other individuals than sentences without a subject. This finding is likely influenced by task demands, as the TAT requires participants to describe photos featuring multiple central characters. This finding was not significant (U = 5784.5, p = 0.6358). Similarly, patients had a higher ratio of first-person pronoun sentences to no-pronoun sentences (1pp:noPro), indicating that they used more utterances about themselves compared to sentences without a subject. This difference, though not statistically significant (U = 4738.5, p = 0.0667), was more pronounced than the difference observed for third-person pronouns and no-pronoun sentences. It could indicate that patients are self-referencing more than they are producing descriptive, pronoun-less utterances. Figure 1 displays the results of measures of perspective taking and mentalization.

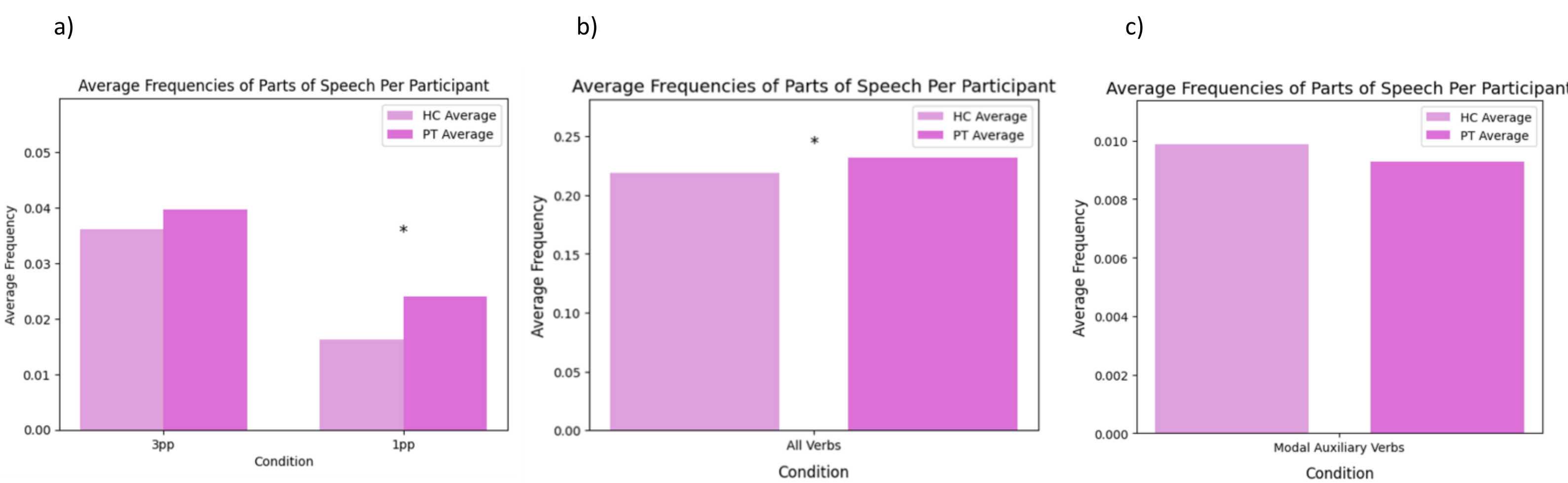


Figure 1. Population average frequencies of parts of speech: a) 3pp and 1pp, b) all verbs, and c) modal auxiliary verbs. Note 1: 3pp = third-person pronouns; 1pp = first-person pronouns; HC = healthy controls; PT = patients. Note 2: * indicates statistical significance between groups.

Emotional Content

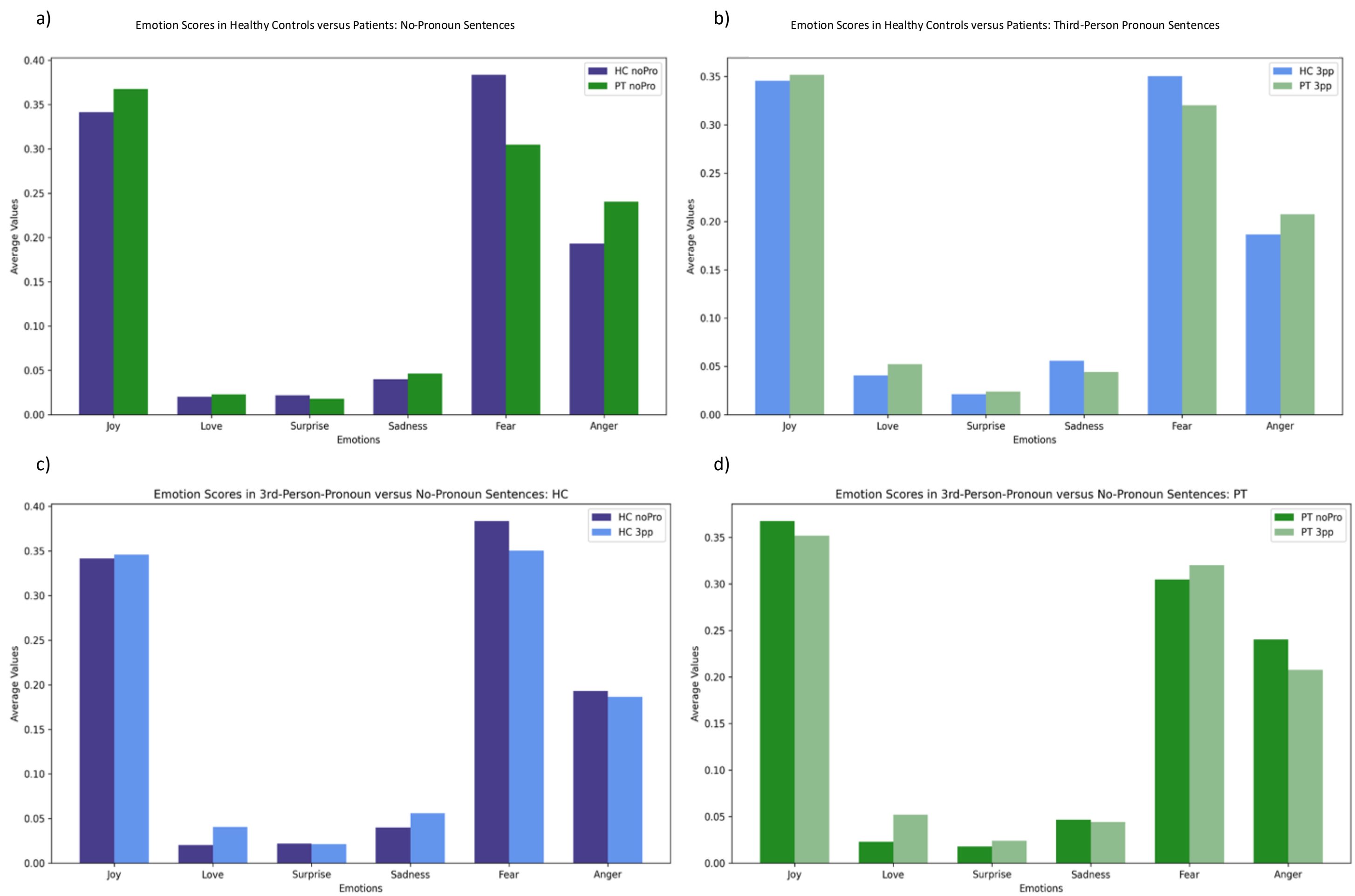
We analyzed emotional content at the sentence level. In the present analyses, we consider just four emotions: love, sadness, fear, and anger, since surprise and joy produced low content across the board and within each group, which we take to be a result of the content of the photos the participants were describing. We compared emotional content in sentences containing no pronouns (the “non-social” condition) to those containing third-person pronouns (the “social” condition) which revealed several significant differences between healthy controls and patients. We consider these findings further in the discussion section. Figure 2 displays the results of measures of emotional content.

No-Pronoun Sentences

Joy content was higher in patients, with this difference reaching statistical significance ($U = 1403571.5$, $p = 0.0366$). Sadness was also higher in patients, but this difference was not significant ($U = 1452660.5$, $p = 0.6774$). Healthy controls expressed more fear, and this difference was significant ($U = 1630498.5$, $p = 1.6255\text{E-}08$). Patients expressed more anger, which was a significant finding ($U = 1345668.5$, $p = 4.8197\text{E-}05$).

Third-Person Pronoun Sentences

Regarding third-person pronoun sentences, several significant differences were observed. Healthy controls expressed sadness and fear to a *greater* extent than patients in the “social” condition, with both differences being statistically significant (Sadness: $U = 737685$, $p = 0.0027$; Fear: $U = 724188$, $p = 0.0289$). Patients expressed joy to a higher extent than controls in this condition, but this difference was not significant ($U = 680811$, $p = 0.6701$). Similarly, patients’ speech captured anger to a greater extent in the “social” content, but this finding was not significant either (U = 676186, p = 0.4812; Love: U = 686117, p = 0.9150).



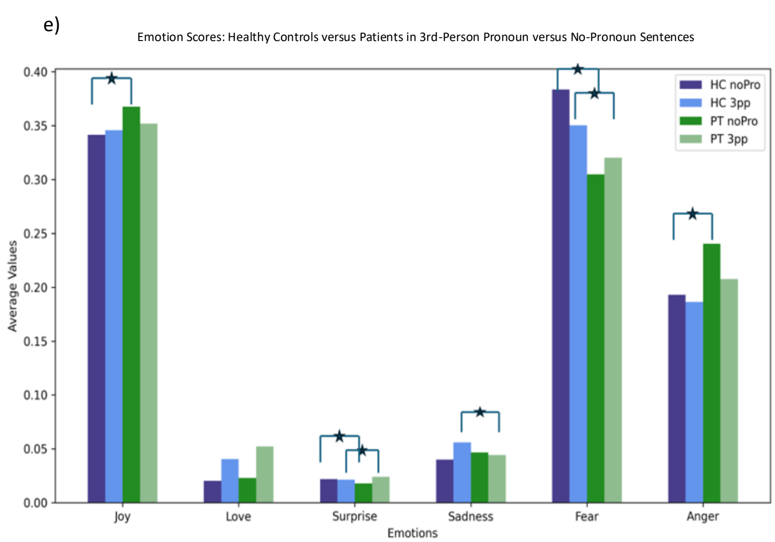


Figure 2. Average emotion score comparisons. The following charts show how emotional content varies between populations and across the “social” (3pp) versus “non-social” (noPro) conditions: a) HC and PT emotion scores in sentences containing no pronouns, b) HC and PT emotion scores in sentences containing a third-person pronoun, c) emotion scores of healthy controls in sentences containing a third-person pronoun versus those containing no pronouns, d) emotion scores of patients in sentences containing a third-person pronoun versus those containing no pronouns, and e) the combined data from charts a-e comparing the two populations (HC and PT) across two conditions (noPro and 3pp sentences).

Note 1: 3pp = sentences containing a third-person pronoun; noPro = sentences containing no pronouns; HC = healthy controls; PT = patients.
Note 2: stars indicate statistical significance between groups or conditions.

Linguistic Complexity

Patients used fewer words than healthy controls, with this difference being statistically significant ($U = 7220.5$, $p = 0.0003$). In contrast, there was no significant difference between the two groups in terms of the average number of sentences ($U = 6194$, $p = 0.1680$). Patients used slightly fewer total sentences on average than healthy controls (averages: patients = 33.20, controls = 30.77).

Significant differences were found in number of words per sentence. When considering *all* sentences, patients had fewer words per sentence compared to healthy controls, and this difference was significant ($U = 6266733$, $p = 1.13356E-12$). Similarly, when examining words per sentence in first-person pronoun sentences, patients again used fewer words per sentence compared to healthy controls, with the difference being statistically significant ($U = 298329$, $p = 0.0001$). In contrast, patients used slightly more, words per sentence in third-person pronoun sentences (averages: patients = 17.99, controls = 17.03), but no significant difference was observed between the two groups ($U = 683743$, $p = 0.8028$). For sentences without any pronouns, patients again used fewer words per sentence than healthy controls, and this difference was also significant ($U = 1706938$, $p = 1.39377E-16$). Figure 3 displays the results of measures of linguistic complexity.

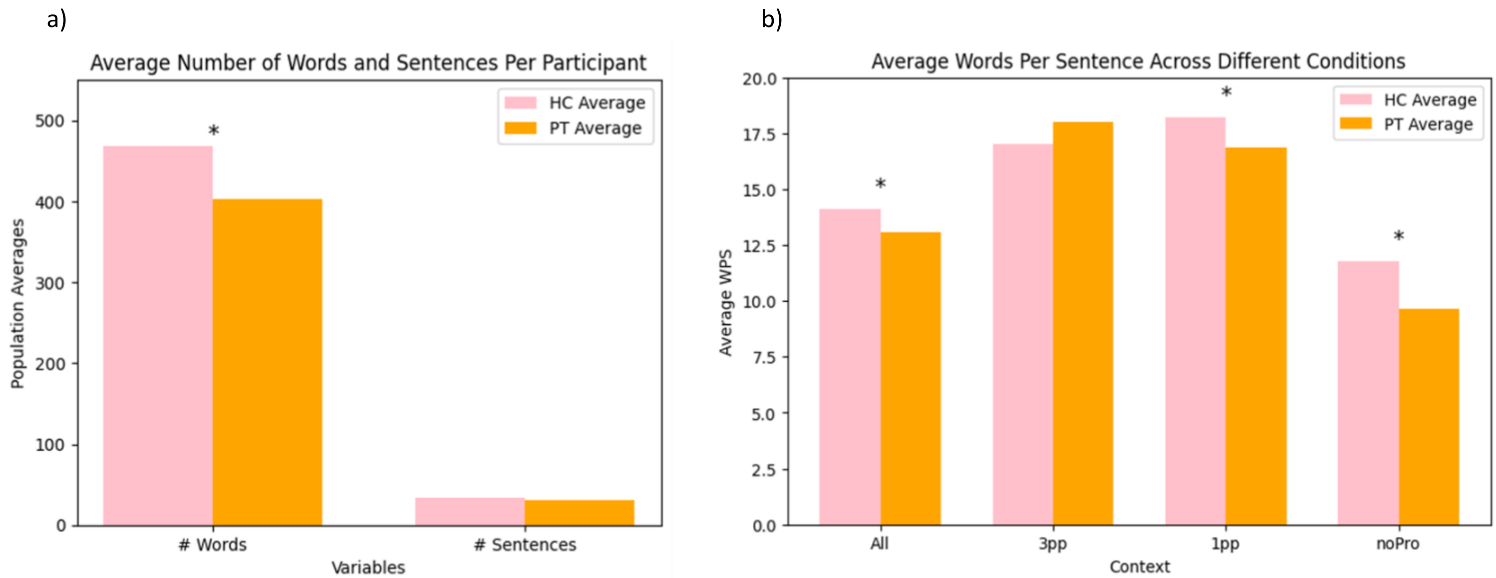


Figure 3. Linguistic complexity measures. Comparison of HC and PT results for: a) the average number of words and average number of sentences per participant, and b) the average number of words per sentence used by HC and PT in four conditions: all sentences, sentences containing a third-person pronoun, sentences containing a first-person pronoun, and sentences containing no pronouns. Note 1: 3pp = sentences containing a third-person pronoun; 1pp = sentences containing a first-person pronoun; noPro = sentences containing no pronouns; HC = healthy controls; PT = patients. Note 2: * indicates statistical significance between groups.

Table 2. Summary of Population Averages and Statistical Test Results for Each Variable

Component	Variable	Test Statistic	*p*-value	Degrees of Freedom	Cohen's *d*	Effect Size (Cliff's Delta)	Effect Size (Rank-Biserial Correlation)	HC Average	PT Average	Significant
Perspective Taking and Mentalization	Verb Frequency	-3.0220371	0.002811142	218	-0.4266712			**0.21888536**	**0.23153148**	**Yes**
	Third-Person Pronoun Frequency	5085.5	0.28574573			-0.086901876	0.086901876	0.03616696	0.03974731	No
	First-Person Pronoun Frequency	4093	0.001117762			-0.265104587	0.265104587	**0.01627258**	**0.02405672**	**Yes**
	Modal Auxiliary Verb Frequency (standardized by total words)	5971	0.375360968			0.072089056	-0.072089056	0.00986641	0.00929396	No
	Modal Auxiliary Verb Frequency (standardized by number of verb phrases)	6363.5	0.079397783			0.142562169	-0.142562169	0.0567729	0.04781801	No
	Ratio of First- to Third-Person Pronouns	4896.5	0.159720895			-0.114556962	0.114556962	0.54911772	0.88006884	No
	Ratio of Third-Person Pronouns to No-Pronoun Sentences	5784.5	0.635769313			0.038603106	-0.038603106	0.77049993	0.90269625	No
	Ratio of First-Person Pronouns to No-Pronoun Sentences	4738.5	0.066670996			-0.149205494	0.149205494	0.46345109	0.77913292	No
	Ratio of First-Person Pronouns to Total Verbs	234964	0.000722574			0.1044453	-0.1044453	**0.35843053**	**0.39985528**	**Yes**
	Ratio of Third-Person Pronouns to Total Verbs	652456.5	0.037031164			0.04985015	-0.04985015	**0.41380646**	**0.4411178**	**Yes**
	Ratio of First-Person Pronouns to Modal Auxiliary Verbs	20292.5	0.79448419			-0.012145244	0.012145244	1.18813906	1.22493225	No
	Ratio of Third-Person Pronouns to Modal Auxiliary Verbs	16248.5	0.079020441			0.095748233	-0.095748233	1.47350993	1.68872549	No
Emotional Content	Joy Score - 3pp sentences	680811	0.670050262			-0.010292328	0.010292328	0.34561746	0.35176904	No
	Anger Score - 3pp sentences	676186	0.481162409			-0.017015777	0.017015777	0.18645044	0.20758749	No
	Sadness Score - 3pp sentences	737685	0.002728144			0.072386468	-0.072386468	**0.05584734**	**0.04422012**	**Yes**
	Surprise Score - 3pp sentences	729220	0.012869806			0.06008074	-0.06008074	**0.02128797**	**0.02401073**	**Yes**
	Fear Score - 3pp sentences	724188	0.028925427			0.052765627	-0.052765627	**0.35025929**	**0.32022408**	**Yes**
	Love Score - 3pp sentences	686117	0.914996893			-0.002578897	0.002578897	0.0405375	0.05218853	No
	Joy Score - noPro sentences	1403571.5	0.03663084			-0.041840787	0.041840787	**0.34150781**	**0.36753796**	**Yes**
	Anger Score - noPro sentences	1345668.5	4.81966E-05			-0.081368729	0.081368729	**0.19287345**	**0.2403311**	**Yes**
	Sadness Score - noPro sentences	1452660.5	0.677379965			-0.008329792	0.008329792	0.04003809	0.04673124	No
	Surprise Score - noPro sentences	1570122.5	0.000331835			0.071856574	-0.071856574	**0.02182106**	**0.01781088**	**Yes**
	Fear Score - noPro sentences	1630498.5	1.6255E-08			0.113072729	-0.113072729	**0.38350164**	**0.30476164**	**Yes**
	Love Score - noPro sentences	1432683.5	0.272550708			-0.021967249	0.021967249	0.02025794	0.02282718	No
Linguistic Complexity	Words per sentence - all sentences	6266733	1.13356E-12			0.101497077	-0.101497077	**14.0953107**	**13.0707699**	**Yes**
	Words per sentence - 3pp sentences	683743	0.802756992			-0.006030025	0.006030025	17.0267666	17.9904956	No
	Words per sentence - 1pp sentences	298329	0.000136927			0.118417797	-0.118417797	**18.2203065**	**16.8796477**	**Yes**
	Words per sentence - noPro sentences	1706938	1.39377E-16			0.165254759	-0.165254759	**11.7743133**	**9.66942529**	**Yes**
	Number of Words per Participant	7220.5	0.000268275			0.296435946	-0.296435946	**468**	**402.134752**	**Yes**
	Number of Sentences per Participant	6194	0.168035344			0.112128557	-0.112128557	33.2025316	30.7659574	No

Note 1: HC = healthy controls; PT = patients; 3pp = third-person pronoun; noPro = no-prounoun; 1pp = first-person pronoun. Note 2: all variables, with the exception of "verb frequency" in the first row, were evaluated using the Mann-Whitney U Test, so the test statistic refers to the corresponding *U*. "Verb frequency" was evaluated using the Student's *t*-test, so the test statistic reflects the corresponding *t*- statistic.

Discussion

In this study, we successfully employed computerized methods to detect features of social cognition in our text samples. The methods detected many of these features with enough precision to produce results that are consistent with the literature. Further, we explored these features in various contexts. Many of these contextualized findings are intriguing and provide a basis for further exploration particularly in future studies looking to stratify social cognitive symptomology in patients with psychotic disorders.

Pronoun Use

Consistent with previous research, we found that patients exhibited a significantly higher use of first-person pronouns compared to healthy controls indicating a higher tendency to self-reference (Figure 1; Table 2). Notably, this pattern emerged despite task instructions that required participants to observe photographs containing *other* characters and describe what they saw, which does not typically require the use of first-person pronouns.

The literature on third-person pronoun use is more varied, but it suggests that patients with psychotic disorders tend to use fewer third-person singular pronouns and more third-person plural pronouns (Bae et al., 2021; M. F. Chaves et al., 2023; Fineberg et al., 2015; Strous et al., 2009). In the current investigation, we did not distinguish between third-person singular and third-person plural pronouns. Quantifying *all* third-person pronouns, however, we observed slightly higher use of third-person pronouns in patients, although this finding was not statistically significant (Figure 1; Table 2). Given that the task involved describing photos that included multiple figures, this may have encouraged participants to use third-person plural pronouns more frequently and could have contributed to patients' increased use of third-person pronouns.

We also examined the frequency of modal auxiliary verbs—standardized by the total number of verb phrases—as these are considered important for social cognition (Tang et al., 2023). Because modal verbs express obligations, possibilities, and intentions, they are thought to be relevant to mentalizing. Although the finding was not significant, we observed that patients used fewer modal verbs relative to their total number of verb phrases than healthy controls (Figure 1; Table 2). This suggests that while patients used more verbs overall, the proportion of those verbs that reflect mentalization was noticeably lower compared to controls.

We used POS tagging to generate frequency counts for the specified parts of speech. Our analysis of first-person pronouns demonstrates that this computerized method can accurately quantify pronoun use, effectively distinguishing between patients and healthy controls, with results that reflect the robust findings on first-person pronoun use in existing studies that used non-computerized methods (Bersudsky et al., 2005; M. F. Chaves et al., 2023; Strous et al., 2009; Zomick et al., 2019).

Additionally, our findings on verb and third-person pronoun use suggest that examining subsets of these parts of speech could yield meaningful insights. For instance, while patients exhibited significantly higher use of verbs in general, controls exhibited a higher—though not statistically significant—use of modal verbs, aligning with expectations (Figure 1; Table 2). These results indicate that broad categorizations of parts of speech may obscure meaningful patterns. Overall, POS tagging proved effective in identifying pronouns and verbs relevant to social cognition within text samples, successfully capturing significant differences between populations.

In addition to conducting frequency counts for each part of speech, we explored relationships among different parts of speech. Quantifying commonly analyzed units of speech in relation to one another yielded findings that point to novel possibilities for computerized methods. Notably, we examined the ratio of first-person pronouns to third-person pronouns within each individual's text sample (Table 2). While patients demonstrated a higher frequency of third-person pronouns compared to healthy controls, they showed a higher first- to third-person pronoun ratio compared to controls. Considering that all participants had the same amount of time to produce speech, this ratio suggests that patients are referencing themselves more often than others which is what we might expect from a population with impaired social cognitive abilities. More nuanced comparisons in the use of POS could thus enhance our ability to represent and analyze social cognition in text.

We also analyzed modal verb use in relation to first- and third-person pronouns. Although patients displayed only slightly higher modal verb frequency compared to healthy controls (modal verb frequency averages: healthy controls = 0.0715, patients = 0.0757), they used fewer modal verbs relative to their use of both first- and third-person pronouns (Table 2). This result indicates that in general, patients are assigning modal, or "socially relevant" verbs, to subjects much less than healthy controls. Again, this finding underscores the potential benefits of particular POS comparisons and reflects one of the goals of our study: to explore diverse ways of implementing computational analyses to uncover nuanced insights into social cognition. While the overall frequency of modal verbs is comparable in patients and healthy controls, their comparative use appears to be different. This suggests that analyzing the relative frequencies of first- and third-person pronouns in relation to modal verbs could be a valuable approach for future studies.

Emotional Content

We analyzed emotional content at the sentence level, focusing on the variation in emotion scores between phrases containing no pronouns (the baseline, or "non-social” condition) and phrases containing third-person pronouns (the "social" condition). Our analysis focused on four emotions—joy, fear, sadness, and anger—since the other two emotions, love and surprise, were consistently low across all conditions and groups, likely due to the nature of the photo content.

Overall, we observed notable differences in the distribution of emotion scores both between groups and between conditions. First, three of the four emotions (joy, fear, and anger) showed significant differences in the non-social (no pronoun) condition between healthy controls and patients. This suggests that the usage of each emotion could indeed be influenced by a factor related to patient status and that our methods were sensitive to this difference (Figure 2; Table 2).

When comparing groups across conditions, an interesting pattern emerged: for three of the four emotions (joy, sadness, and fear), patients and controls demonstrated opposite trends between the non-social and social conditions (Figure 2; Table 2). Although not all these trends were statistically significant, they reveal that patients and controls are expressing emotions differently in *different contexts*. For instance, healthy controls displayed a *decrease* in fear from the non-social to the social condition, while patients exhibited an *increase* (Figure 2; Table 2). Additionally, where patients experienced an increase in fear from the baseline to the social condition, they showed a corresponding decrease in joy, whereas controls demonstrated the reverse pattern (Figure 2). This particular finding aligns with the existing literature, which has repeatedly shown that patients with psychotic disorders tend to attribute more negative or hostile emotions to others than healthy controls (Buck & Penn, 2015; Cho et al., 2017; Corcoran & Cecchi, 2020; Gao et al., 2021; Lyons et al., 2018; Zomick et al., 2019). Specifically, in phrases mentioning a third person ("another person"), patients expressed increased fear, whereas controls showed a decrease. These results not only reflect previous findings but also highlight the influence of social context on emotional expression. This underscores the value of integrating perspective-taking methods with emotional content analyses.

Another key observation was that in the social context, patients had significant lower scores on fear and sadness than controls (Figure 2; Table 2). This suggests that patients may struggle to express these emotions to the same extent as controls in social settings. Collectively, these observations demonstrate that healthy controls and patients express emotions differently depending on context. Thus, both patient status and the context of the discourse (social or non-social) influence emotional content in speech. Applying computational analyses of emotional expression highlights the importance of considering context when analyzing emotional content, as patients' emotional expressions vary from that of healthy controls not only in general but also across different settings. Future studies aiming to capture expressions of social processing through automated emotion analyses should incorporate context-specific approaches to advance text-based analyses of social cognition as these features might more precisely distinguish among populations.

Linguistic Complexity

We found that patients produced significantly fewer total words than healthy controls, with patients averaging 402.13 words and healthy controls 468 words (Figure 3; Table 2). This was the case despite the fact that both groups produced a similar number of sentences (healthy controls: 33.20 sentences, patients: 30.77 sentences) (Figure 3; Table 2). Each participant was given equal time to elaborate on what they observed in the photos and was encouraged to use the entire time. The fact that patients produced fewer words but a similar number of sentences during this time suggests that they elaborated less on each thought or utterance, which aligns with findings in the literature with respect to reduced linguistic complexity (Andreasen, 1979; Bedi et al., 2015; Corcoran et al., 2018; Elvevåg et al., 2010; Hoffman et al., 1985; Kircher et al., 2018; Lim et al., 2020; Parola et al., 2023; Rezaii et al., 2019; Tan et al., 2014).

While this study does not aim to establish direct links between linguistic complexity and impairments in social cognition, shorter utterances may limit both the quantity and quality of social-cognitive content conveyed in each phrase. To explore this further, we analyzed words per sentence—a key proxy of linguistic complexity—across various contexts related to perspective-taking. Specifically, we calculated words per sentence for all sentences and for sentences containing a third-person pronoun, a first-person pronoun, or no pronoun at all.

Our findings revealed that patients used significantly less words per sentence than healthy controls in three contexts: all sentences, sentences with first-person pronouns, and sentences without pronouns (Figure 3; Table 2). However, in the third-person pronoun condition, both groups produced a similar number of words per sentence, with patients averaging slightly higher (healthy controls: 17.03 words, patients: 17.99 words) (Figure 3; Table 2). This difference, however, was not statistically significant.

These basic indices of linguistic complexity are in line with previous findings that patients produce fewer total words and fewer words per sentence overall (Andreasen, 1979; Bedi et al., 2015; Buck & Penn, 2015; Corcoran, Mittal, Bearden, Gur, et al., 2020; Elvevåg et al., 2010; Hoffman et al., 1985). Additionally, we compared linguistic complexity in social and non-social contexts (Figure 3b). In contrast to our findings related to emotion processing where we observed differences across the social and non-social context, here there was reduced complexity in *both* the social and the non-social context in patients. Evaluating complexity in different contexts of text may thus be of limited value for computational methods aimed at extracting features of social cognition from text.

The Thematic Apperception Test

Finally, our findings suggest that the Thematic Apperception Test (TAT) is an appropriate tool to use in conjunction with computational methods for analyzing social cognition. Our ability to extract meaningful social information from the text samples was dependent on whether the TAT produces a corpus of text that provokes sufficient speech related to social-cognitive thought process. We used this test because the photos depict multiple characters engaged in various actions, often in thought-provoking contexts. It thus disposes participants to produce speech with social content. Other researchers have already employed the TAT for similar purposes (Inslegers et al., 2012; Sinclair et al., 2023; Stein et al., 2012). Although this study does not directly measure the ability of the TAT to evoke social discourse, it is plausible that the results produced by our computational analyses are contingent on the richness of TAT images. This is a valuable consideration for future studies that want to use a semi-controlled speech sample. This test is particularly appealing for its ability to engage participants in discourse naturally—allowing them to speak freely—while simultaneously providing a controlled sample, as all participants describe the same images in the same timeframe. Based on our success in detecting group differences with TAT-produced text, we conclude that this task indeed produced speech samples relevant to our scientific aims. Still, while we believe the speech samples provided valuable insights, comparing the text dataset produced by the TAT to other tasks or text samples would offer a deeper evaluation of its performance.

Limitations

One of the primary goals of this study was to determine whether computational methods can reliably detect features of social cognition in text. We observed significant group differences in many analyses, suggesting that our approach captured some patterns in the text. However, to make more robust claims, it is essential to incorporate external measures of social cognition aligned with the specific features examined here. Such measures would allow us to better evaluate whether our computerized methods accurately and reliably capture social cognitive processing.

Another limitation is the lack of other computational measures to compare with our results. For example, one could use other methods for extracting emotional content, such as sentiment analysis or applying the NRC Emotion Lexicon (Mohammad & Turney, 2013), and ask whether the results of these methods converged with those present here. The NRC Emotion Lexicon also provides information about the attribution of the six basic emotions with a methodology different from the context-driven BERT-based language model used here. It would, therefore, provide an interesting comparison. Additional comparisons would help to evaluate the robustness of our results, and they could also serve as complementary tools if used together with our method. To achieve the same depth of analysis for social cognition in text as is possible for other symptoms in this population, continued exploration of computational approaches for perspective-taking, emotional content, and linguistic complexity is necessary. Further, confounding factors such as patient status (e.g., clinical and familial high risk, first-episode psychosis, and long-term treatment), gender, and medication were not addressed in this study. These factors can stratify the data and may impact the findings. Finally, breaking the task down by analyzing responses to individual photos could reveal gradients in emotional content and provide a broader perspective on how and when these features emerge in speech.

Future Directions

In this study, we grouped patients with varying statuses—including clinical and familial high-risk individuals, first-episode psychosis patients, and those with over three years of treatment—based on findings suggesting that impairments in social cognition are observable across all these groups (Green et al., 2012; Kohler et al., 2014; Oliver et al., 2021; Stanislawski et al., 2021; Tang et al., 2017). However, it is possible that these groups differ in the severity or nature of their social impairments. For instance, patients in one phase may exhibit reduced perspective-taking abilities, while those in another phase might produce distinct emotional content. Future research should revisit these analyses within individual patient groups to better understand which methods are most effective and to determine whether specific analyses should be tailored to particular patient statuses. These more nuanced findings would be applicable to the problem of stratifying symptomology for more targeted treatment and predicting illness trajectory at various stages.

Additionally, the emotion recognition algorithm employed in this study introduced a novel approach to analyzing emotional content in text for this clinical population. However, no independent benchmarks were available for emotional content to compare with our findings. Future studies should consider incorporating sentiment analysis techniques that assess dominance, valence, and arousal ratings, along with tools like the NRC Emotion Lexicon

(Mohammad & Turney, 2013), which associates words with the six basic emotions. These approaches are unlike the BERT-based contextual language analysis used here and might offer complementary insights. We suggest comparing these methods with the current approach and exploring whether the information they provide can be used in conjunction with, or in place of, some of the emotion data provided from our method to create richer emotional profiles. This would significantly enhance the overall quality of the method and further the progress toward leveraging social cognition in text. By refining computational text analysis to achieve greater accuracy and reliability we can unlock its full potential for advanced applications.

Conclusion & Summary

Our objective was to determine whether we can use computational methods to detect features of social cognition in text samples that are capable of distinguishing between patients with schizophrenia spectrum disorders and healthy controls. To this end, we explored various methods to quantify the presence of features falling under three domains of social cognition: perspective-taking and mentalization, emotional content, and linguistic complexity. We further explored whether combining and contextualizing these features could provide insight into novel features of social cognition that could be used in computational text analyses. We met this objective with several significant findings and some suggestive trends. By pairing and contextualizing features, some additional interpretations arose.

Notable findings emerged in perspective-taking, emotional content, and linguistic complexity. Patients demonstrated a significantly higher use of first-person pronouns, consistent with prior research, but relatively lower use of modal verbs compared to their total verb phrases, indicating less mentalization. Contextual analyses, such as the ratio of first- to third-person pronouns and modal verbs assigned to pronouns, revealed nuanced differences in social cognitive expression. In emotional content, significant baseline differences in joy, fear, and anger between patients and controls were observed, with patients expressing more negative emotions in social contexts, such as increased fear when referencing others. Contextual differences between social and non-social conditions underscored the influence of patient status and discourse type on emotional expression. Regarding linguistic complexity, patients produced fewer total words and shorter utterances, reflecting reduced elaboration, though both groups displayed similar complexity when referencing others. These findings confirm that we successfully selected computational methods and meaningful ways to apply them to detect social cognitive features in text capable of distinguishing between patients with psychotic disorders and healthy controls, with emotional content and perspective-taking measures offering particularly valuable insights.

In summary, this work has leveraged the connection between language and cognition with the aim of advancing the way it can be used in understanding, diagnosing, and treating psychotic disorders. By applying computational methods such as those from computational linguistics and natural language processing, this study addresses key limitations of traditional clinical tools, offering a more objective, scalable, and nuanced approach to analyzing language in psychiatric contexts. Specifically, this research aimed to work toward the identification of *features of social cognition* in text, a largely unexplored area in psychosis research. By distinguishing patients with psychotic disorders from healthy controls, these methods not only promise improved diagnostic precision but also pave the way for tailored treatment strategies and enhanced predictive modeling of illness trajectories. This exploratory work offers a number of valuable insights for the continued advancement of computational tools into psychiatric practice, fostering more nuanced results and more effective interventions for affected individuals.

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