Understanding language abnormalities and associated clinical markers in psychosis: The promise of computational methods

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Abstract

The language and speech of individuals with psychosis reflects their impairments in cognition and motor processes. These language disturbances can be used to identify individuals with and at high-risk for psychosis, as well as help track and predict symptom progression, allowing for early intervention and improved outcomes. However, current methods of language assessment – manual annotations and/or clinical rating scales – are time intensive, expensive, subject to bias, and difficult to administer on a wide scale, limiting this area from reaching its full potential. Computational methods that can automatically perform linguistic analysis have started to be applied to this problem and could drastically improve our ability to use linguistic information clinically. In this paper, we first review how these automated, computational methods work and how they have been applied to the field of psychosis. We show that across domains, these methods have captured differences between individuals with psychosis and healthy controls and can classify individuals with high accuracies, demonstrating the promise of these methods. We then consider the obstacles that need to be overcome before these methods can play a significant role in the clinical process and provide suggestions for how the field should address them. In particular, while much of the work thus far has focused on demonstrating the successes of these methods, we argue that a better understanding of when and why these models fail will be crucial towards ensuring these methods reach their potential in the field of psychosis.

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Individuals with psychosis have a number of impairments in cognition[1,2] and motor processes[3–6]. Language production – communicating with others through speech, written text, or sign – is a domain that is severely disrupted by these impairments[7,8]. Individuals with psychosis exhibit disorganized speech that can be off topic, drift from the original thought, or be incoherent or difficult to follow[9,10]. Speech by individuals with psychosis can be vague and repetitive, as well as reduced in quantity and syntactic and lexical complexity[11–15]. In addition, individuals with psychosis differ in their vocal characteristics from healthy individuals. For example, they often speak with a flat affect – sometimes producing emotionally intense thoughts in a disconnected way[16,17]. Many of these language disturbances are characteristic symptoms of psychosis, contribute to worse outcomes, and are evident in early stages of psychosis, even before formal onset[18–20].

These language disturbances are helpful in identifying individuals at high-risk for and with psychosis, allowing for early intervention, as well as for tracking and predicting symptom progression[12,18,21,22]. However, several practical issues limit this area from meeting its full potential. Specifically, language is currently assessed via manual annotation by expert raters and/or clinical rating scales. These data are highly time-intensive to gather – making it impractical to use these methods on a wide scale – and rely on rating scales that may be underpowered, making it difficult to pick up on anything but the most extreme versions of these impairments.

Computational methods could drastically improve the ability to use linguistic information clinically, providing a scalable method for using language in a more objective, reliable, and replicable way. In this paper, we will first review how these automated, computational methods work and how they have been applied to the field of psychosis, by reviewing preliminary yet promising findings in this area. As will become clear, across many studies, using many different methods, at many different levels of language, computational methods have been shown to capture differences between individuals with psychosis and healthy controls, and have been able to categorize speech samples as belonging to either group at rates of 70-100%[23–30,21].

However, despite their initial promise, there are substantial hurdles to overcome before computational methods can play a significant role in the clinical process. In the second part of the paper, we argue that while much of the work thus far has focused on demonstrating the successes of these methods, critical evaluation of when and why these models fail will be crucial towards ensuring these methods reach their potential in the field of psychosis.

Why care about language?
Observed impairments in language production in psychosis

In this section, we review empirical work demonstrating what abnormalities individuals with psychosis exhibit, as well as their clinical and neuropsychological correlates. We focus on three main types of disturbances: (1) disorganized speech (positive thought disorder), (2) poverty of speech (negative thought disorder), and (3) flat affect. Lexical abnormalities (e.g. increased use of non-words or word approximations) are also present in psychotic disorders, but as they are less frequent, less understood neuropsychologically, and less studied from a computational perspective (but see Gutierrez et al.[31]), we do not focus on them here. Within each of these four categories, Table 1 provides definitions and examples of specific subtypes.

Positive Thought Disorder (Disorganized Speech)

Disorganized speech has been found to correlate with other positive symptoms of psychosis, primarily delusions[32–34]. While the underlying causes are not yet fully understood, and may vary between individuals[35], disorganized speech is argued to be related to deficits in semantic memory and abnormal semantic associations between words[36–39], working memory, attention, and other executive function deficits[40] (but see Bagner et al.[41]), and/or failure to incorporate linguistic context (possibly due to executive function deficits)[42–44]. Neurally, severity of disorganized speech is associated with reduced grey matter in the superior temporal and inferior frontal cortices[45] (but see Palaniyappan et al[46]) and abnormal activation in superior temporal cortex[47–49] during both free speech production and semantic priming tasks. Finally, while disorganized speech is associated with poorer outcomes and role functioning, it is often considered to be less persistent and less prognostically useful than negative thought disorder[18,19,32,50].

Negative Thought Disorder (Poverty of Speech/Content and Reduced Syntactic Complexity)

Negative thought disorder correlates with other negative symptoms, is predictive of age of onset of psychosis, and is prognostic of future outcomes (i.e. transition to psychosis, being psychotic at follow-up)[51–55] and social role functioning[56]. It is associated with impairments in lexico-semantic retrieval[57] as well as working memory deficits. Neurally, patients who produce less complex sentences showed weaker activation in the right temporal and left prefrontal cortex[14], and negative thought disorder is associated with gray matter reductions in the orbitofrontal and insular cortex[45,46].

Speech and Conversation: Flat Affect and Pausing

Flat affect predicts course and outcome of the illness 20 years after initial hospitalization[58,59], and is associated with worse quality of life[59] and poorer social functioning[60]. Studies examining individuals with flat affect as measured through facial expressivity and emotion processing show that the severity of flat affect is associated with reduced activity in the amygdala, parahippocampal gyrus, as well as multiple regions of the left prefrontal cortex[61]. Flat affect has been shown to correlate with other negative symptoms (e.g. negative thought disorder).

Not all individuals with psychotic disorders exhibit these abnormalities; furthermore, some healthy individuals do: in an extreme case, one study found that 32% of healthy individuals exhibited 'tangentiality' in 50 minutes of speech vs. 50-60% of the patient group[62]. Additionally, these abnormalities need not co-occur within individuals: studies investigating the co-occurrence of negative and positive thought disorder have found weak correlations at best ($r = 0.23$), and sometimes observe an inverse relation ($r = -0.32$). As a result, these abnormalities should be approached dimensionally rather than as categorically present vs. absent[53].

In spite of this heterogeneity, we note that each type of language abnormality has predictive clinical value. However, language has been underused as a signal in clinical evaluations. This is likely due to the subtlety of some of these abnormalities, as well as the reliance on time-intensive, manual evaluations or holistic clinical ratings. Computational methods may provide a way to capitalize on the predictive value of language abnormalities.

Measuring abnormalities in language production using automated, computational methods

Desiderata

The goal of the computational approaches we review is to provide quantitative measures of the severity of these language abnormalities given a speech/language sample. We evaluate this body of work for (i) construct validity, or evidence that the automated measures are indeed measuring the language abnormalities they are designed to (e.g., by comparing them to human ratings, by showing that systematic changes in language lead to systematic changes in measures, or by qualitatively demonstrating the sorts of sentences that score high/low), (ii) theoretical validity, (iii) replicability, (iii) generalizability and equity, and (iv) predictive value, or evidence that these measures relate to symptoms, functional outcomes, neurocognitive measures, behavior, etc., so they can lead to targeted intervention or treatment. However, we note that equally important in these early stages of development is critical evaluation of where models fall short of these standards and promising directions for improvement.

Obtaining speech samples

The first step in any analysis is obtaining the relevant data. Currently, most studies gather data in clinical or research settings (e.g. in a therapy session, at an in-patient hospital, or in a research lab). Speech can come from clinical assessments or be elicited by a variety of prompts, e.g.: “Could you tell me about your favorite hobby and how one does it?”; “Tell me the story of Cinderella”; or prompts relating to personal experiences. The benefit of this approach is that the investigator can simultaneously collect demographic and symptom information from participants, which can lead to nuanced and particularly informative analyses. More recently, computational linguists have turned to social media, finding users who declare a psychosis diagnosis, and collecting other posts of theirs on unrelated topics, which they contrast against analogous posts by individuals who do not report a diagnosis[63,64]. This method allows access to large language samples of text produced by many users, including those who may not otherwise seek help – but does not allow for analysis of speech, nor for systematic clinical measurement.

Computational methods

With these data in hand, researchers have applied a number of computational techniques to measure a variety of linguistic abnormalities. We focus on the most studied methods, but list other promising methods in Table 1.

Measuring disorganized speech

Vector representations

Latent semantic analysis (LSA) and word embedding models (e.g., word2vec, GloVe) have been used to obtain measures of disorganized speech (i.e., measures of derailment, tangentiality, coherence). These methods provide a measure of how similar phrases are to one another and have been applied to psychosis research with the idea that more coherent and less derailed speech will, on average, have phrases that are more similar to one another than less coherent texts. These methods first represent each word in the text as a vector – a list of numbers. Roughly speaking, these vectors represent the contexts in which a word is used; words with similar meaning will appear in the same context. For example, ("king"/"queen") are likely to co-occur in similar articles and, consequently, have similar vectors, whereas dissimilar words ("broccoli"/"shoe") are less likely to co-occur and, consequently, will have less similar vectors (Figure 1). Word vectors are combined to obtain phrase-level vectors (e.g. by averaging word vectors); similarity of the phrase vectors is used to get measures of disorganization (e.g. by measuring how similar adjacent sentences are or how dissimilar subsequent sentences get from the participant's first sentence; see Figure 2).

As shown in Table 2, studies using these methods show considerable promise, finding that (i) disorganization scores are significantly higher for individuals with psychotic disorders than controls[23,29,30], (ii) disorganization scores correlate with manual holistic ratings of disorganization[23,28], and (iii) disorganization scores, in combination with other factors, can predict conversion to psychosis or discriminate patients vs. controls with accuracies around 70-100%, sometimes even outperforming classifications based on clinical symptoms scales (i.e. SIPS)[28,29,65].

Despite this initial promise, this research area faces key challenges. As of yet, no consistent measure of disorganization has yielded reliable findings across multiple papers (e.g., Bedi et al.'s and Elvevåg et al.'s implementations did not work on the Iter et al. sample). It is hard to interpret these inconsistent results as papers have used different categorization methods (Table 2; "Classification") and different ways of obtaining word vectors, have studied different subsets of measures (Table 2; "Study") and have applied them to small, heterogeneous, sometimes poorly-controlled samples (e.g. age in Iter et al.; Table 3).

Existing measures of disorganization are also difficult to interpret. While these computational measures correlate with human judgments, it is still unclear what aspect(s) of the complex construct of disorganization dissimilarity measures reflect. These interpretive difficulties are critical because measures of disorganization sometimes *do not* correlate with positive symptoms (but see Bedi et al.[65]) – but *do* correlate with other confounds like age[28] (older participants exhibited less disorganized speech) and sentence length[29] (shorter sentences are rated as more disorganized). Relatedly, measures of disorganization are typically just one of many other variables in categorization models, so it is difficult to quantify the unique contribution of disorganized speech. While these methods show considerable promise, more validation work is clearly needed.

Measuring poverty of speech and content

Word graphs

Mota and colleagues have used word graphs to measure differences in speech between individuals with schizophrenia, mania, and healthy controls. The structure of speech is represented by linking word nodes based on their order and then using established measures of graph connectivity and complexity (e.g. number of nodes/edges/loops, length of longest path) to obtain thought disorder scores. These measures show group differences between schizophrenia, bipolar disorder, and control participants[66,67], correlate with negative symptoms[67,68], can predict the presence of psychosis six months later[68], and relate to differences in neural measures[69]. The performance of these measures is impressive; however, it is not yet clear what abnormalities these measures reflect (i.e. positive thought disorder vs. negative thought disorder), and how theoretically valid they are.

Vector unpacking

Rezaii and colleagues used a method called vector unpacking to automatically measure poverty of speech content (vague, repetitive, or non-substantive speech)[70]. They examined whether sentence vectors could be well-approximated by other vectors composed of fewer words (e.g., the meaning of *The president flew to China on a plane* is well-approximated by *The president flew to China;* the corresponding sentence vectors are likely to be very similar). This measure could categorize which CHR adolescents would convert to psychosis with accuracy exceeding 80%[70], correlated with negative symptoms and non-expert human ratings, and was shown to outperform related measures such as idea density (roughly the density of content words) and information value (roughly the average sentence vector length). This measure shows particular promise as it was individually tested on a held-out dataset and was well-validated against clinical scales and human judgments; future work should test its generalizability.

Syntactic parsing

Speech by individuals with psychosis often exhibits reduced syntactic complexity[11–14,71]. This has primarily been studied by automatically tagging each word in a text with its part-of-speech information (e.g., noun, verb) and counting the number of subordinated clauses individuals use[72–74]. For example, in addition to the semantic coherence measures described above, Bedi and colleagues found that reduced density of determiner pronouns (e.g. 'that', 'what', 'whatever'), reflecting fewer subordinated clauses, was associated with worse symptom severity[26]. Similarly, Corcoran and colleagues showed that reduced possessive pronoun (e.g. 'her', 'his', 'mine') counts improved performance of their model of CHR conversion[28]. However, these measures have not been considered independently of disorganization measures, so the relative role that each plays is not yet clear.

Measuring flat affect and abnormal pausing

The methods described above focus on what is said and, thus, can work off of written transcripts of speech. To measure flat affect, researchers have used automated methods to analyze *how* individuals speak, studying the acoustic characteristics of their vocal productions, as well as pausing behavior. We briefly review some promising results (e.g., classifying psychosis vs. control samples at 70-94% accuracy[25,27]) here. However, we note that a recent meta-analysis[75] has documented substantial heterogeneity in the findings across both computationally-oriented and manual annotation studies, making it clear that there is much work to be done in this area.

Researchers have automatically measured mean pitch (i.e. fundamental frequency, F0), as well as pitch variability, of speech by individuals with psychosis vs. healthy controls. Some have found that individuals with psychosis have reduced pitch variability relative to controls[27,76] and that within the psychosis group, reduced pitch variability is associated with worse negative symptoms[77]. However, other studies have not found this relationship[25,78]. Other studies have automatically measured the mean and variance of formant values (a measure of spectral properties of speech, largely determined by the shape of the vocal tract). Some studies found that individuals with psychosis exhibit decreased variability in the first two formant values, and that decreased variability in formants is associated with worse negative symptoms[76–79], but others have failed to replicate these findings[80]. Additional work in this area has shown that individuals with schizophrenia speak at a slower rate[27,79,81], show less variability in syllable timing[27], and show decreased variability in loudness/intensity[25,76]. In addition to acoustic differences, individuals with psychosis have also shown abnormal conversational turn-taking relative to controls, pausing more often and for longer[25,27]. Between-turn pauses have also been associated with worse positive symptoms in youth at high-risk for psychosis, but showed no significant differences between high-risk and control participants[20].

Meta-analyses of this body of work have documented substantial heterogeneity in the results. Across five studies, Cohen et al.[82] found no meaningful differences between patients and controls after controlling for sociodemographic and contextual factors. Parola et al.[75] reviewed

55 studies (1254 schizophrenia, 699 controls), and found modest, variable effects of pause duration, pitch variability, spoken time, speech rate, and number of pauses (with some evidence of publication bias).

Recent literature has begun investigating the puzzling discrepancy between the size of group differences as measured by acoustic measures vs. clinical ratings of blunt affect (the construct that these acoustics are thought to measure). Researchers have suggested that these measures operate at "different resolutions," with clinical ratings providing holistic measures of an entire interaction, while acoustic measures zoom in on sub-portions. This may allow for more nuanced understanding of flat affect, though more work needs to be done to validate this suggestion[83].

Additional factors could contribute to the heterogeneity in findings. Acoustic analyses currently require that speech be recorded under very good conditions, such that different recording conditions can make different studies incomparable. In addition, much of the work on vocal characteristics has attempted to measure flat affect; however, other factors that have not been accounted for could lead to voice differences. For example, some individuals with psychosis exhibit motor difficulties, which would likely affect their articulations, and in Andreasen & Grove's sample[62], between 16-32% of individuals with schizophrenia exhibited pressured speech, which would have the opposite impact on vocal productions than flat affect. The heterogeneity in results could simply reflect the heterogeneity in mechanisms involved, so more systematic, hypothesis-driven study is required to tease these factors apart and better understand what these measures reflect.

Exploratory analyses

While the previous methods have studied well-documented language abnormalities in psychosis, investigators have also adopted a more exploratory approach to see whether individuals with psychotic disorders differ from controls in the topics they discuss and words they use, primarily focusing on social media language[63,64,84–86]. Some of these studies[84] have used Linguistic Inquiry and Word Count (LIWC)[87], which counts the proportion of words that fall within certain pre-defined categories (e.g. negative or positive affect, anxiety). Others have used topic modeling[63,74], which automatically discovers which topics participants discuss[88] without prespecifying them. Some of the most promising and consistent results suggest that individuals with psychosis use more function words (e.g. 'the', 'a'), first person singular pronouns (e.g. 'I'), auxiliary verbs, negative emotion words, insight words, and health words, but show a decreased focus on leisure[63,64,84–86]. However, there has been substantial variability in findings, with sometimes opposing effects. For example, of five papers, two papers[84,85] found that controls used more first person plural pronouns ('we') than the psychosis group, but another[86] found the opposite, and the remaining studies reported no difference between groups. In addition, the use of social media data means that these results cannot be linked with symptomatology.

Moving forward

Across domains of language structure and use, computational methods have shown promise in being able to identify the linguistic properties that differentiate individuals with psychosis from healthy controls. But there are clear challenges that the field must address, especially given its high social impact. It can be difficult to evaluate how well these methods are measuring linguistic abnormalities due, in part, to an overreliance on categorization methods.

Discrepancies in findings across studies undermine confidence that these methods are generalizable.

How can we move forward? Much of the work thus far has focused on the successes of these methods; an increased focus on when and why these methods fail will help refine our work. A great deal of research has been exploratory in nature; adopting a more hypothesis-driven approach that relates these automated measures to other known, relevant measures in psychosis will help ground these methods in the wider psychosis literature. Finally, we emphasize the importance of considering sociodemographic factors front and enter when evaluating these models, especially in light of an extensive literature documenting that computational methods magnify biases. We discuss each of these in turn.

Difficulty evaluating performance

Overreliance on categorization

Much of the past work has focused on developing functions that categorize patients as having (or developing) psychosis or not. While this is important work, overly focusing on categorization creates several interrelated issues. Given the dimensional aspect of these abnormalities -- not all patients exhibit these abnormalities, some healthy individuals do, and some patients exhibit opposite patterns of impairment (e.g. alogia vs. pressured speech, derailment vs. perseverance/repetition) -- it is unclear how to evaluate classification accuracy. It is unlikely one can classify based solely on speech/language, and the true target accuracy is likely to vary between studies. On the other hand, categorization functions are very likely to “overfit” the data – that is, learn and rely on spurious differences between the (necessarily limited size) psychosis and control groups that do not necessarily generalize to other datasets, an issue exacerbated by how heterogeneous the manifestations of psychosis are[89]. This could, in part, explain how some models have achieved 100% on one dataset, while being at chance on another. Finally, overly focusing on categorization makes it difficult to evaluate construct validity. Demonstrating that a measure can categorize individuals into two groups well does not reveal how and why the measure works, as well as what constructs it is tapping in to. Instead of simply focusing on classification accuracy, it may instead be more useful to (i) evaluate computational methods on speech samples that are known to contain (or not) particular linguistic abnormalities, (ii) focus primarily on comparisons with symptoms, behavior, neurocognitive variables, and clinical ratings (less emphasized in past work), and (iii) start to tackle questions about the sensitivity of these methods, how specific they are to psychotic disorders vs. other illnesses, and what the time course of their predictive value is.

Increasing comparability of studies

Although many of the individual papers we report on show promising findings, these findings do not always align with one another. The papers we review have studied different and heterogeneous subgroups (e.g. individuals with schizotypy, CHR youth, individuals with schizophrenia, schizoaffective disorder, mania, individuals with or without thought disorder), in a variety of contexts (hospitals, research labs, on the internet), using different kinds of prompts (written vs. spoken, spontaneous speech vs. read speech, more or less personal questions) that elicited varied lengths of responses. In addition, these studies have made different modeling decisions (e.g. have used different categorization techniques) and have studied different subsets of linguistic variables measured in different ways. Any of these differences could have contributed to the heterogeneity across studies; however, the discrepancies make it difficult to evaluate the generalizability of these methods.

This is why it is critical that computational studies make direct comparisons with past work. To facilitate this, studies should share their analyses so that replications are possible. Direct comparison of results can also be helpful for considering qualitatively different methods. For example, directly comparing word graphs vs. vector-based coherence measures on the same sample would allow for better understanding of what each of the methods is capturing and what their relative benefits are.

Where possible, standardizing elicitation methods for speech and written text, or explicitly considering differences between elicitation methods, would be helpful. It has become clear that different methods result in different speech sample lengths, which can add noise to automatic speech and language measures; this leads investigators to make different modeling decisions (e.g., Bedi et al.[26] vs. Corcoran et al.[28]), further exacerbating differences. Ideally, research would be done on larger samples of data collected specifically for the purpose of analyzing language[90]; barring this, computational models should be run across multiple datasets to ensure that the model is not overly sensitive to idiosyncratic properties of one dataset[26,28–30].

Understanding model failures/successes for model refinement

To improve modeling, there now needs to be a shift away from emphasizing the good performance of models towards more of a focus on where and why these models fail. This can be done by performing detailed error analyses of the systems. In particular, it would be helpful to examine the speech/language tasks that the model incorrectly marked as having high or low levels of a particular abnormality to identify classes of recurring patterns that the model does not handle well. This approach has successfully fueled innovation in analysis methods. Error analyses of particular language samples allowed Iter et al. to realize that methods from Elvevåg et al. and Bedi et al. performed poorly on text that is heavy with verbal fillers (e.g., 'uh', 'like', 'I mean'), heavy with repetitions, and also to realize that sentence length was related to disorganization scores.

In addition to leading to refinements, qualitative analyses of errors can reveal the strengths of methods that might not otherwise have been appreciated. In trying to understand why the biobehavioral measures they studied did not mirror the large effects in clinical ratings, Cohen et al. were able to show a temporal resolution at which their measures did show larger effects. This revealed an additional potential benefit of automated methods – that they can capture differences at resolutions that clinical ratings cannot. Especially at the early stage of development, this type of analysis can help move the field in the right direction (and is currently being more emphasized in computational research for this very reason).

Adopting a hypothesis-driven approach

Most of the research thus far has been data-driven and exploratory in nature. While this work has been promising, more focus on theoretical validity, and direct connections between computational analyses and the broader psychosis literature could help address some of the issues outlined above. For example, acoustic differences that individuals with psychosis exhibit relative to controls could be due to documented motor difficulties[4], differences in how individuals represent particular sounds[91], cognitive difficulties[1], aprosody[76], and so forth. Each of these possibilities makes different predictions about what symptoms, behavioral task performance, or neural abnormalities the changes in speech acoustics should be associated with. This can drive more targeted, well-controlled analyses that will yield more reliable performance with the small, heterogeneous samples that characterize this area of research. By expanding the types of questions being asked beyond categorization, hypothesis-driven work can also clearly improve our understanding of what these linguistic measures reflect.

Bias in computational methods

Sociodemographic factors, such as race, age, education, gender, as well as linguistic and geographical background, have been understudied in relation to automated methods in psychosis. On the one hand, an extensive literature has documented harmful bias in computational methods across domains[92], including in some of the very methods described here: vector embeddings show biases based on race and gender[93,94], automatic speech recognition systems show greater error rates for black speakers than white speakers[95], and facial recognition software currently used is being recalled because of performance disparities[96]. It is critical to ensure the models we describe are not plagued by similar biases.

There is some evidence that they may be. For example, Bedi et al. found an association with age, such that older individuals had more organized speech samples, but age has not been controlled for in most of the reported analyses, even when patients and controls are not matched on age[29]. Similarly, Mota et al.[97] found an association between graph-based speech connectedness and education. In measuring flat affect, researchers have used acoustic cues like formant values and pitch[76–79]; however, these acoustics are affected by a number of other factors, including vowel type, neighboring sounds, dialect, gender, and age[78,98–100] – factors which were not modeled in previous work. In fact, Cohen et al.[82] found that when controlling for social factors and task type, all group differences disappeared. Controlling for potential social factor confounds is clearly a key area for development.

At the same time, it is important to recognize that speech and language measures must ultimately be evaluated in a social context, as what is considered ‘normal’ (e.g. a normal response length to a question) varies drastically by culture. Body language, gestures, and intonation can change how something is perceived, so these methods may ultimately need to be used in conjunction with such measures[101–105]. In addition, most models have been developed for English, and other languages may require different, tailored approaches to measuring the same constructs. Although these issues are by no means unique to automated approaches, models that gloss over cultural/contextual factors could magnify the problem, especially as one of the potential benefits of computational methods is that they can reach a wider range of individuals. The field must confront these issues early and consistently to ensure its benefits reach everyone.

<u>These issues will remain even with improved measures</u>

Computational linguistics is a rapidly developing field. Static word embeddings are being replaced with context-sensitive models (e.g. BERT, ELMo). Automated speech analysis is yielding more accurate measurement of a wider range of acoustic measures. Advances in related areas may allow for these methods to be used in conjunction with automated measures of body language, gesture, facial expressions, and so forth[101–105]. As we capitalize on these advances, we will still need to address the core issues we’ve identified here: compare performance across models, identify their strengths and areas for potential improvement, link model results to the broader psychosis literature (e.g., through hypothesis-driven methods), and inspect models for bias.

Conclusion

Abnormalities in language production are characteristic of psychosis, present prior to disease onset, and can directly contribute to worse outcomes. Computational methods can be used to automatically detect these language abnormalities and have shown great promise in being able to classify and predict psychosis, sometimes outperforming clinical measures. These methods are particularly promising, as they are objective and cost-effective, meaning they could be applied on a wide scale to reach and help individuals who might previously fall through the cracks. Much of the work to this point has understandably focused on demonstrating the successes of these methods. However, to best move the field forward, we argue that the field should now shift focus towards understanding when and why current models fail. Accomplishing this will require collaborations between psychosis researchers, linguists who understand the measures and language abnormalities, as well as computational researchers who can develop and refine these models to be appropriate for this area. By performing qualitative error analyses, testing the generalizability of these models, adopting a more hypothesis-driven approach where possible, and aligning results with decades of psychosis research, we can better adapt these methods to the psychosis domain, to ensure that these methods can be as beneficial for all as quickly as possible.

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