Mental health in remote and rural farming communities

Centre for WHS

WESTERN SYDNEY UNIVERSITY

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Executive summary

Australians living in rural and remote areas face a unique combination of stressors, placing them at elevated risk of mental health problems. They also have poorer access to mental health services than those living in Australian cities. Compounding the problem of fewer available services are barriers to help-seeking, such as stigma and entrenched stoicism. E-mental health services permit spanning great distances and have the potential to circumvent the barriers faced by clients in rural and remote communities using technology. Text-based services are particularly well suited to addressing the needs of Australians in rural and remote communities because they offer a level of anonymity not possible in traditional face-to-face, video-, or audio-based delivery methods, making them appealing to clients concerned with stigma, self- presentation and privacy. Moreover, they allow the client to reflect on the therapy session after it has ended as the transcript is stored on their phone (or another device). The text transcript also offers researchers an opportunity to analyse language use patterns and explore how these relate to mental health status. In this project, we investigated whether computational linguistic techniques can be applied to text-based communications with the goal of identifying a client's mental health status. The results confirmed that word use patterns could be used to differentiate whether a client had one of the top three presenting problems (depression, anxiety, or stress), as well as prospectively to predict their self-rated mental health after counselling had concluded. These findings suggest that language use patterns are useful both for researchers and for clinicians trying to identify individuals at risk of mental health problems, with potential applications in screening and targeted intervention.

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Introduction

Mental health issues are as prevalent in rural areas as they are in urban centres. However, access to psychological services is limited in rural Australia, and self-harm rates increase with remoteness. Innovative approaches to mental health promotion and suicide prevention, such as the services provided by *Virtual Psychologist* (Virtual Psychologist, 2020), have an important role to play in meeting the needs of rural and remote communities. By using technology to span great distances, communication platforms such as text-based counselling provide the desperately needed services to those living in rural regions. However, little is known about how effectively such technology may serve a primary prevention function, that is, as a means of screening and/or early intervention. Nor is it known whether the language within these text exchanges contains linguistic markers that are predictive of future mental status, and thus might serve a prognostic function. This report explores whether language use patterns can be used to accurately predict the mental health status of people living in rural and remote Australia, especially farmers.

Rural Australians are at increased risk of mental health problems

Australians who live in rural and remote communities are at increased risk of adverse health outcomes because they face a combination of chronic, yet unpredictable, stressors. Overall, there are fewer employment opportunities than in urban centres, and a reliance on primary industries leaves rural areas prone to financial instability due to fluctuations in weather conditions, natural disasters (e.g., drought, bushfires, floods, cyclones), commodity and fuel prices, and currency exchange rates (Vins, Bell, Saha, & Hess, 2015). Remoteness increases the risk of mental illness, self-harm and suicide (National Rural Health Alliance, 2017). Relative to urban areas, the suicide rate is 40% higher in rural areas, increasing to 100% higher in remote areas. Suicide rates in both rural and remote areas are also increasing faster than in capital cities (between 2012 to 2016, suicide rates increased by 9.2% outside of capital cities, compared to 2% in capital cities; (Hazell, Dalton, Caton, & Perkins, 2017). Farmers, in particular, are more likely to suicide than other occupations (Andersen, Hawgood, Klieve, Kõlves, & De Leo, 2010; Kennedy, Maple, McKay, & Brumby, 2014; Milner, Spittal, Pirkis, & LaMontagne, 2013). Those most at risk fit the following profile: they are overwhelmingly (> 90%) male, young (*M* suicide age = 41 years), have recently separated or divorced (20%), live alone (33%), are more likely to be farm labourers rather than farm owners or managers, and have a precipitating mental condition (Austin et al., 2018).

Barriers to accessing mental health services

Australians living in rural and remote areas generally have poorer access to, and make less use of, health services than those living in cities. Fewer mental health professionals work in rural and remote areas (70-80% less than in major cities), meaning that it is more difficult for clients to access mental health treatment. The distances involved and the reluctance of at-risk individuals to engage in traditional face-to-face counselling provide further barriers to servicing such communities. Those living in rural communities may be reluctant to seek counselling services due to stigma and community gossip, as well as entrenched stoicism and views that help-seeking is a sign of weakness (Judd et al., 2006; Perceval, Ross, Kõlves, Reddy, & De Leo, 2018).

In recent decades, technological advances have led to the implementation of e-mental health services that can circumvent some of the above barriers. Such e-mental health services have the potential to make a valuable contribution to service delivery in rural areas (Benavides- Vaello, Strode, & Sheeran, 2013). Some e-mental health approaches seem particularly well suited to individuals reluctant to seek help due to stigma and stoicism. One such service is synchronous text-based counselling, which involves the simultaneous participation of two parties (e.g., a client and a therapist) who engage in real-time communication (e.g., via SMS, WhatsApp, and/or internet chat). There are two aspects of text-based counselling that are likely to appeal to farmers living in rural and remote communities: 1) the anonymous nature of text- based interactions; and 2) low-bandwidth delivery across great distances eliminates the need for transport or high levels of internet connectivity.

A small number of studies have explored the reasons some people are more likely to engage in (and benefit from) text-based counselling. Evidence suggests that people generally disclose emotions similarly when using technology as compared with face-to-face communication (Derks, Fischer, & Bos, 2008) and that text-based communication enables some people to better express their true-self qualities (Bargh, McKenna, & Fitzsimons, 2002) or to disclose more personally confronting topics (Stubbings, Rees, & Roberts, 2015).

A consistent observation across studies is that text-based counselling takes longer than phone counselling (Fukkink & Hermanns, 2009a; King, Bambling, Reid, & Thomas, 2006), and generates fewer words than verbal exchanges (Rodda & Lubman, 2014). Some patients have expressed negative views related to the less fluid interactions, reduced content covered, and impatience while waiting for the therapist to respond. Clients who prefer face-to-face or phone conversations have described text-based communication as too distant or impersonal. Others found the time delays created space to think and reflect, and to communicate feelings without being disrupted by further questioning, as might occur in face-to-face sessions (Beattie, Shaw, Kaur, & Kessler, 2009). Those who viewed text-based counselling positively appreciated the distance, anonymity, security, privacy, and control over self-presentation, which is especially relevant for those with emotional problems (Fukkink & Hermanns, 2009b).

The effectiveness of text counselling

Text-based counselling has been shown to be as effective as traditional face-to-face counselling for a variety of conditions including depression (DellaCrosse, Mahan, & Hull, 2019; Kramer, Conijn, Oijevaar, & Riper, 2014), anxiety (Cohen & Kerr, 1999; DellaCrosse et al., 2019), and emotional problems (Fukkink & Hermanns, 2009a, 2009b). Therapist-guided internet- delivered treatments are effective in treating a range of mental health conditions, and can be as effective as face-to-face treatments (Andersson, 2016; Andersson, Carlbring, Titov, & Lindefors, 2019; Andersson, Rozental, Shafran, & Carlbring, 2018). E-mental health services with a text-based component are effective in treating substance abuse, including problematic alcohol consumption (Blankers, Koeter, & Schippers, 2011) and cannabis use (Schaub et al., 2015), as well as in reducing undesirable behaviours, including high-risk sexual behaviours in young homosexual men (Lelutiu-Weinberger et al., 2015), and in improving sense of coherence, self-esteem, and subjective quality of life in young adults with ADHD and/or autism (Wentz, Nydén, & Krevers, 2012).

Text-based delivery has been rated as better than or equal to face-to-face therapy on a number of dimensions, including convenience, effectiveness, making progress with problems, and having access to help when needed (Hull & Mahan, 2017). It should be noted, however, that text-based counselling may not the optimal mode of service delivery for all clients (King et al., 2006), and that clients who do not engage with text-based therapy will not show clinical improvement (Crutzen, Bosma, Havas, & Feron, 2014; Kordy et al., 2016). In summary, text- based counselling is a promising therapeutic approach that can be an effective alternative to face-to-face and phone-delivered therapy (for reviews, see Dowling & Rickwood, 2013; Hoermann, McCabe, Milne, & Calvo, 2017), and the increased anonymity and privacy may make some segments of the population more likely to engage in, and reveal greater and more truthful information within therapeutic interactions.

Computational linguistic analyses of the text-based counselling transcript

Text-based counselling generates a transcript that documents the exchanges during the therapeutic process. This transcript offers possibilities that are not available to other service delivery methods: it, of course, permits the client and therapist to re-read and reflect on their communication after the session has ended; it also opens up the research possibility of conducting analyses on text transcripts to identify linguistic patterns. There is an emerging literature suggesting that language use patterns are reliable predictors of mental health status. Few studies have linguistically analysed texts from individuals at-risk of mental health problems. The majority have mined social media (Babu, 2018; De Choudhury, Gamon, Counts, & Horvitz, 2013; Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017; Ruiz et al., 2019; Schwartz et al., 2014) or online forums (Al-Mosaiwi & Johnstone, 2018; Davcheva, 2018; Fekete, 2002; Park, Conway, & Chen, 2018) to identify linguistic patterns that might be predictive of mental health status.

This work has been enabled by the development of computational linguistic tools, the most widely used of which is the Linguistic Inquiry and Word Count or LIWC (Pennebaker, Boyd, Jordan, & Blackburn, 2015; Tausczik & Pennebaker, 2010). LIWC categorises and counts words, and offers an overview of the statistical distribution of words within pre-defined and psychologically meaningful categories. The capabilities of LIWC (and other similar programs or algorithms) have led researchers to explore the language use patterns of individuals with depression and other mental health conditions. Numerous studies have shown that an increased use of first-person singular pronouns (e.g., *I, me, my, mine*) is indicative of depression (Fast & Funder, 2010; Molendijk et al., 2010; Pyszczynski & Greenberg, 1987; Rude, Gortner, & Pennebaker, 2004; Weintraub, 1981), severity of depression and anxiety (Brockmeyer et al., 2015; Zimmermann, Brockmeyer, Hunn, Schauenburg, & Wolf, 2017), general proneness to distress or negative emotionality (Lyons, Aksayli, & Brewer, 2018; Tackman et al., 2019), and suicidal ideation (Stirman & Pennebaker, 2001). These promising findings suggest that language use patterns could conceivably serve as predictors of mental health with potentially clinically significant applications.

There is a dearth of studies that have analysed text-based counselling transcripts. Nevertheless, the results from this small number of studies suggest that this may be a potentially fruitful avenue for future research. Dirkse, Hadjistavropoulos, Hesser, and Barak (2015) found that greater use of negative emotion, anxiety and sadness words positively correlated with heightened anxiety; greater use of negative emotion, sadness, and anger words positively correlated with heightened depression; and greater use of negative emotion and anger words positively correlated with heightened panic. Compatibly, use of negative emotion words predicted symptom improvement in outpatients being treated for personality disorders (Arntz, Hawke, Bamelis, Spinhoven, & Molendijk, 2012), and use of discrepancy words (e.g., *would*, *should*, *wish*, *hope*) reliably predicted depression improvement (Van der Zanden et al., 2014). Depressed patients who used positive emotion words early in treatment tended to have good treatment outcomes, whereas use of past focus words was associated with poor treatment outcomes (Huston, Meier, Faith, & Reynolds, 2019). Such results suggest that word use may be used to determine an individual's psychological condition and future prognosis.

Owen et al. (2005) examined word use in a support intervention for women with early-stage breast cancer. More frequent use of words expressing anxiety and sadness (but not anger) were significantly correlated with improved emotional well-being at follow-up, whereas greater expression of sadness (but not anxiety or anger) was associated with improved quality of life.

Although this is an emerging research area, the level of sophistication in the analyses is rapidly improving. Seabrook, Kern, Fulcher, and Rickard (2018) were able to reliably predict depression severity using negative emotion word instability, and interestingly, they created an emoji and internet slang supplement to the LIWC dictionary which increased the accuracy of depression identification. Additionally, it may soon be possible to combine demographic, linguistic, behavioural, and social data so as to construct sophisticated models to identify at- risk individuals (see Calvo, Milne, Hussain, & Christensen, 2017).

The present study

There is evidence that language use patterns may be useful for identifying mental health conditions. This would be particularly beneficial for underserved populations where mental health risks are elevated but where service provision is low. To date, most studies examining the relationship between language use and psychological presenting problems have provided a static view into the presence (or absence) of a single condition, such as depression, and in some cases its severity. However, in order to identify individuals at-risk of mental health problems, it is necessary to detect several of the most common psychological conditions and to reliably differentiate them.

Taking advantage of a NSW Government funded initiative that provides text-based counselling to Australians in rural and remote communities, through the *Virtual Psychologist* service (Virtual Psychologist, 2020), the major aim of this study was to demonstrate the feasibility of using linguistic patterns in text-based counselling transcripts to predict whether an individual was suffering from depression, anxiety or stress. The analysis was conducted with the LIWC software tool (Pennebaker et al., 2015) on the transcripts of counselling sessions conducted over a one year period and provided by *Virtual Psychologist* through the NSW Government Centre for Work Health and Safety. The study also investigated whether language patterns were predictive of self-rated mental status.

Method

Human Ethics Statement

This study was conducted in full compliance with the National Statement on Ethical Conduct in Human Research and approved by the Western Sydney University Human Ethics Committee (Approval no.: H13309).

Participants

The participants were 320 clients of the *Virtual Psychologist* counselling text-based counselling service (https://www.virtualpsychologist.com.au) who used the service between August 2019 and September 2020, for one or more sessions. All participants lived in rural or remote communities across Australia. Data from participants aged < 18 years was excluded. The participants completed a short demographics questionnaire concerning their age range, gender, state, and presenting mental health concerns (as described in the Results section below).

Materials

The data was provided on a monthly basis by *Virtual Psychologist* to the researchers through the NSW Government Centre for Work Health and Safety. The data consisted in Excel spreadsheets containing the text of the chat sessions, with metadata giving the date and time of each interaction as well as limited demographic information about the participant. Another spreadsheet contained the answers to the client survey (see Procedure section below).

The Linguistic Inquiry and Word Count (LIWC) tool (Pennebaker et al., 2015) is the most widely used corpus of dictionaries for computational linguistic analyses of text data. It is a software program containing algorithms that enable it to count words belonging to different categories. To achieve this, LIWC compares words within an input text file to those within its dictionary. The output offers an overview of the statistical distribution of words within a text into pre-defined categories, including function words, pronouns, impersonal pronouns, verbs, auxiliary verbs, and past tense words.

To meet the aims of the current project, the LIWC dictionaries were customised to suit the Australian data set. To achieve this, Australian spellings were added to the standard LIWC American spellings (e.g., *agonise/agonize*), and where necessary, equivalent Australian words were also added (e.g., *mobile/cellphone*). The Australianised dictionary is described in Appendix A.

Procedure

Participants were provided with the service terms and conditions at the first point of contact with the *Virtual Psychologist* service. The terms and conditions address the provision of information collected to third parties in a de-identified format. By agreeing to the above, participants gave consent to be included in the research project and accessed the service. Participants then completed a short demographic survey, which was de-identified (e.g., postcode was used to classify region of residence as either regional, rural or remote). Text transcripts of counselling sessions between participants and therapists were also de-identified (i.e., names of people, workplaces, landmarks etc. were removed). After each session, each participant received an SMS with a link to a short client survey concerning their experience with the *Virtual Psychologist* service. This contained the single-item self-rating of mental health "*How would you rate your mental health now?"* on a 5-point scale ranging from "poor" to "excellent" (see Appendix B).

Data processing

To ensure compatibility with LIWC, the text data were pre-processed (cleaned and normalised) and restructured using the MATLAB software. Chat sessions containing fewer than 30 words were removed (e.g., sessions the client initiated but did not engage in, perhaps due to mobile phone connectivity issues or work-related/personal interruptions). The final data set comprised 773 sessions involving 270 participants. Figure 1 shows the workflow for the data processing and analyses.

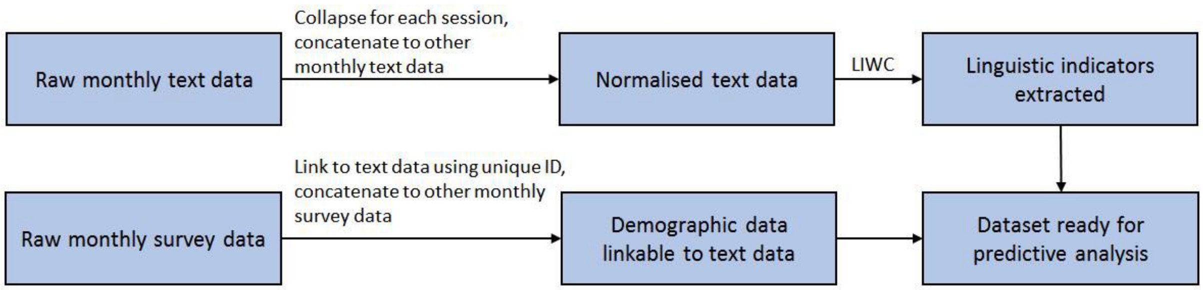

Figure 1. Workflow for the data processing and analyses.

Data analysis

Following the workflow described in Figure 1, various linguistic indicators were extracted for each session using LIWC (Pennebaker et al., 2015; Tausczik & Pennebaker, 2010). Further data analyses were conducted by exploring the relationships between the linguistic patterns in the chat sessions and the participant's self-reported psychological concerns at service entry, and their mental well-being self-rating after having received counselling. Of all possible linguistic indicators, the following 21 indicators were selected as independent variables (predictors) to be used in the predictive analysis: word count, analytical score, clout score, authenticity score, emotional tone, first-person pronouns, positive emotions, negative emotions, causation, insight, discrepancy, social processes, functional words, other words, affect, cognitive processes, drives, personal concerns, focus past, focus present and focus future. Participants' self-reported mental health problems at service initiation and self-rated mental well-being from the survey were treated as dependent variables in the predictive analysis.

Several methods can be used to determine whether linguistic patterns can accurately classify participants into one of the top three presenting problems: discriminant analysis, logistic regression, neural networks, support vector machines, and classification trees. Each method places differing requirements on data and eligibility, and the algorithm underlying each method also varies, leading to differences in performance when applied to different research questions. In this study, discriminant analysis was deemed best suited to the needs of the prediction analysis required to answer the research questions. Discriminant analysis is used when the research question aims to predict group membership or classify cases into groups on the basis of a set of predictor variables. It has been widely used in many language and psychology studies (Burget, Matejka, & Cernocky, 2006; Covic, Tyson, Spencer, & Howe, 2006; Egbert & Biber, 2018; Escudero, Simon, & Mitterer, 2012; Etkin et al., 2015; Feeney, Connor, Young, Tucker, & McPherson, 2006; Flowers & Robinson, 2002; Hills & Argyle, 2002; Martin, Altarriba, & Kazanas, 2020; Soenens, Duriez, & Goossens, 2005), and for binary classification in particular, it has been shown to have higher discriminant power than other methods (Maroco et al., 2011).

Results

Throughout the course of the project, detailed presentations were made of the linguistic characteristics of the data sample (see Milestone 2, Deliverable 2 Linguistic Analysis), as well as of the statistical techniques that can categorise clients into presenting problems based on language use patterns (see Milestone 2, Deliverable 3 Predictive Analysis). The results of the linguistic and predictive analyses reported here incorporate the final client data as received on 21 September 2020.

Sample Description

The text data employed in the analyses reported here were collected between August 2019 and September 2020; they consist of 1,154 text-based counselling sessions from 320 participants who engaged with the *Virtual Psychologist* service. Following data cleaning and pre- processing, the final data set comprised 773 sessions from 270 participants. The distribution of sessions per participant is presented in Figure 2.

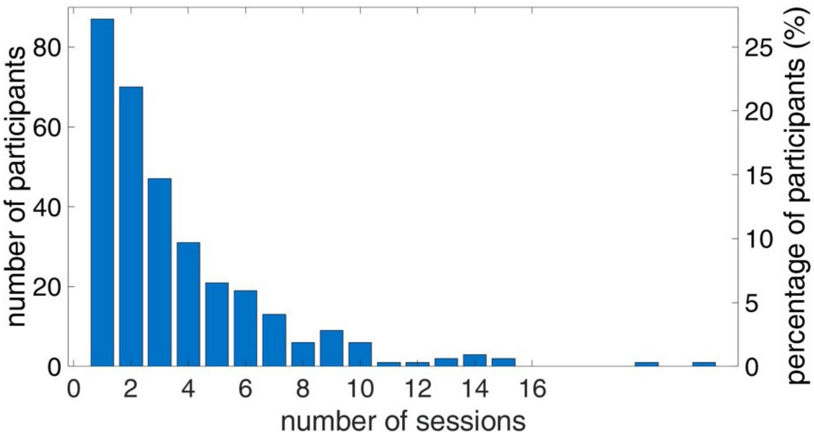

Figure 2. Distribution of the number of text-based counselling sessions completed by each of the 270 participants. 90% of participants completed between 1-7 sessions

On average, participants completed 3.6 sessions of text-based counselling; there was however considerable variability in the number of sessions completed. Most participants (90.0%) engaged in 1–7 sessions, although some engaged in as many as 22. Approximately one quarter (27.2%) of participants engaged in only a single session. For each session, the client sent 11 messages on average (ranging from 1–84). The total number of words per session also varied widely. An average session contained 357 words communicated between therapist and client. This is consistent with literature reporting that text-based chat is slower than verbal communication and results in fewer words being exchanged between conversational partners (Fukkink & Hermanns, 2009a; King et al., 2006).

Data collection commenced in August 2019, however, as shown in Figure 3, the number of monthly sessions increased from March 2020 onward. This was likely precipitated by two events:

- First, Australia suffered from unprecedented bushfires in late 2019, extending into early 2020, and rural areas were the most badly affected;
- Second, the first confirmed case of COVID-19 in Australia was identified on 25 January 2020 (Australian Government, 2020), resulting in Australian borders being closed to non-residents on 20 March, and government restrictions (social distancing rules, closing of nonessential services) put in place on 21 March 2020.

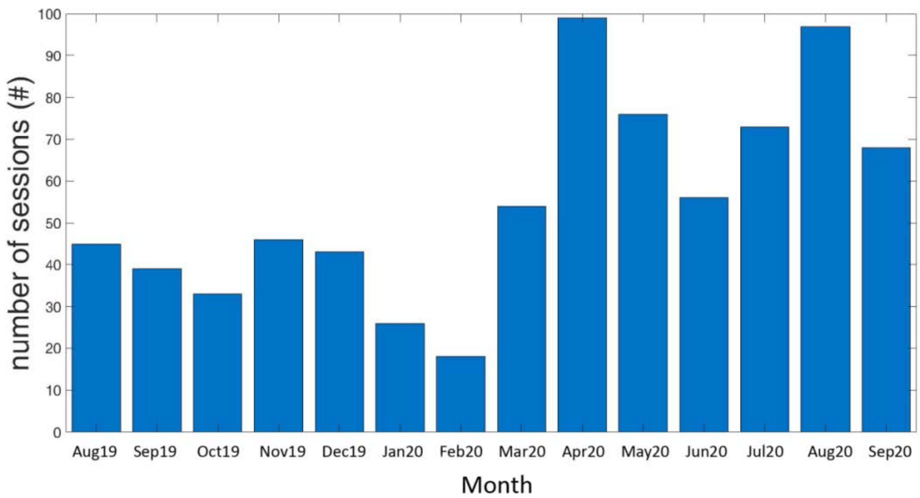

Figure 3. Number of text-based counselling sessions completed by participants each month from August 2019 to September 2020

In terms of sex, the majority of participants were female (*n* = 167, 61.8%). As shown in Figure 4, females outnumbered males three to one, and also completed more sessions. 44 (16.3%) participants did not disclose their sex.

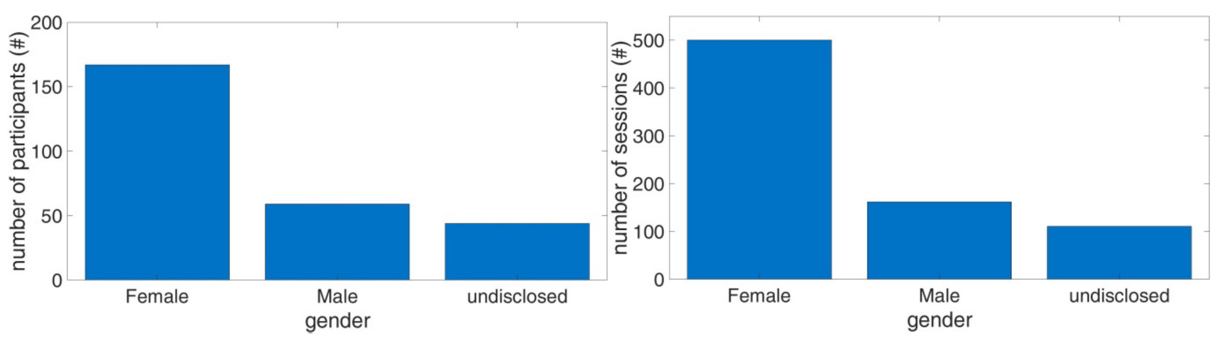

Figure 4. Number of participants (left panel) and number of sessions (right panel) for each gender.

The age distribution of participants is shown in Figure 5. The sample was primarily comprised of adolescents and young adults (age ranges 18–21 and 22–29). This is consistent with reports that individuals who are comfortable using technology are more likely to engage in text-based counselling. Interestingly though, the discrepancy between 18–21 and 30-40-year-olds decreases when we inspect the number of sessions completed, suggesting that the average 30– 40-year-old engaged in a greater number of counselling sessions than the average 18–21-year- old. This is encouraging, as 41-year-old males are most at-risk of serious mental health problems and suicide. Older adults were fewer in number, and on average engaged in fewer sessions than their younger counterparts (2.0 sessions).

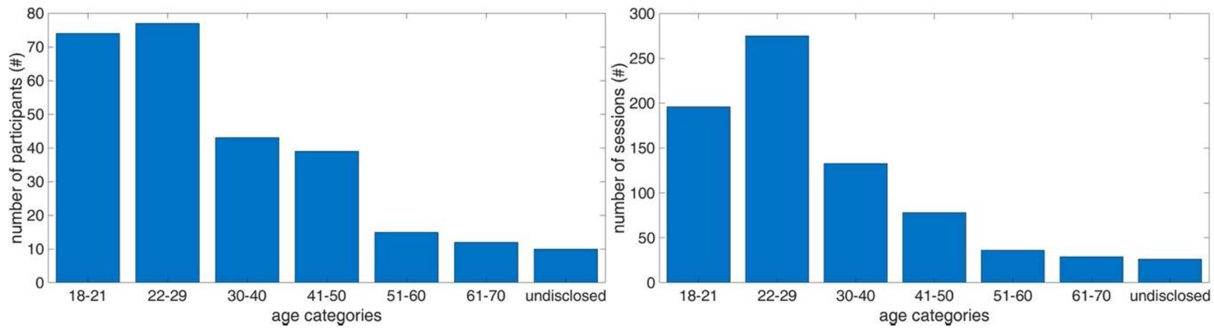

Figure 5. Participants' age distribution (left panel) and the number of sessions completed by each age category (right panel).

In terms of geographic location, participants came from six Australian states (Figure 6). The vast majority were from rural and regional NSW, and the second most represented state was Queensland. For the other states, participants from Victoria and Western Australia, although in smaller number, tended to engage in more sessions than those from South Australia and Tasmania.

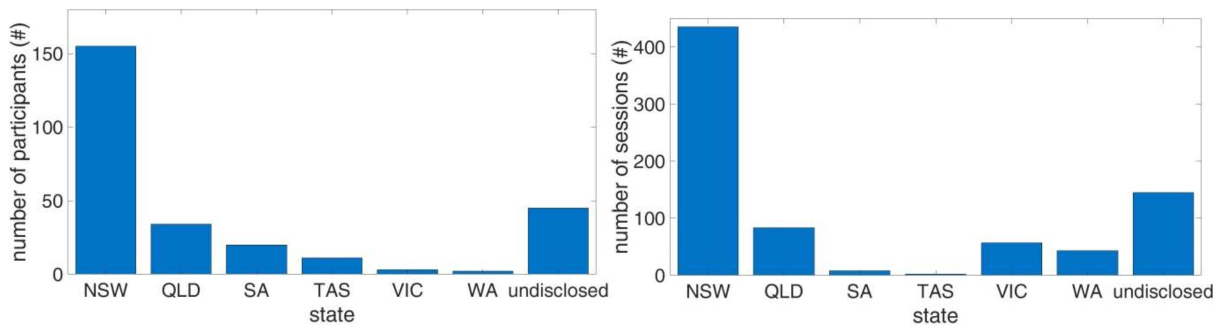

Figure 6. Number of participants (left panel) and number of sessions (right panel) from each Australian state.

Upon referral to the *Virtual Psychologist* counselling service, each participant's self-reported mental health concern ("presenting problem") was recorded (Table 1). The top three mental health conditions which clients presented with were anxiety, depression and stress, and comprised about half of the total number of sessions. Approximately one quarter of all sessions fell into the "other" and "undisclosed" categories, suggesting that even for an anonymous and privacy-focused method of e-mental health service provision, there remain a considerable number of individuals for whom disclosure, and presumably stigma, remains an issue (though not a barrier to seeking help).

Table 1. Presenting problems that led participants to seek counselling expressed as a distribution of the number of text-based counselling sessions completed.

Presenting Problem	No. of sessions
Anxiety	152
Depression	143
Stress	61
Family Issues	50
Relationship Issues	49
Grief and Loss	25
Trauma Issues	15
Suicidal Thoughts	13
Anger	6
Work Problems	6
Domestic Violence	4
Isolation/Loneliness	4
Critical Incident	3
Self Harm	3
Covid-19	2
Eating Disorders	1
Friend Issues	1
Health Concerns	1
LGBTI Issues	1
Physical Abuse	1

Note that participants with undisclosed presenting problems (n = 179) are not listed.

For the 773 sessions completed, 165 (21.3%) responses were recorded to the single-item self-rating of mental well-being "*How would you rate your mental health now?*" on a 5-point scale ranging from "poor" to "excellent". As shown in Figure 7, most participants chose "fair", although responses varied widely, and made use of the full range of response options available.

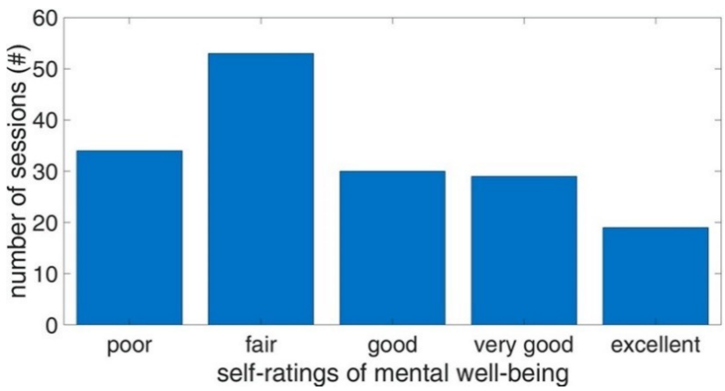

Figure 7. Participant responses to the single-item self-rating of mental well-being "How would you rate your mental health now?" on a 5-point scale ranging from "poor" to "excellent".

Linguistic Analysis

The four basic LIWC word counts are shown in Table 2: analytical thinking, clout, authenticity, and emotional tone.

Table 2. Descriptive statistics of LIWC word counts and scores for the basic summary variables of analytical thinking, clout, authenticity, and emotional tone. Summary variable scores range from 1–99.

Indicators	Mean	Median	Min	Max
Analytical thinking	24	19	1	95
Clout	34	28	1	99
Authenticity	75	86	1	99
Emotional tone	57	60	1	99

The distributions for these four basic LIWC dimensions are depicted in Figure 8. Analytical thinking scores (top left panel) had a shallow positive skew, with the majority of those scores falling within the range 0–50. This indicates that participants were using a language style similar to a narrative, focused on their personal experiences. Note that higher analytical thinking scores are associated with better academic performance in tertiary education (Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014). The observed concentration of scores on the other half of the scale appears to be a valid representation of the sample population being studied, that is, farmers living in rural areas.

Clout refers to social status, confidence, or leadership (Kacewicz, Pennebaker, Davis, Jeon, & Graesser, 2013). Clout scores (top right panel) had a shallow positive distribution and were somewhat more evenly distributed across the range of scores. This may reflect different ranks or responsibilities within the sample, such as farm labourers versus farm managers and owners.

Authenticity scores (bottom left panel) had a sharp negative distribution. Higher authenticity scores indicate truthfulness, humility and vulnerability (Newman, Pennebaker, Berry, & Richards, 2003; Pennebaker, 2011). Encouragingly, this indicates that the vast majority of participants were using language associated with being truthful. This is consistent with literature suggesting that text-based counselling offers a high degree of privacy and anonymity, giving users time and space to select the right words to express themselves (Beattie et al., 2009; Fukkink & Hermanns, 2009b) and reveal more truthful information (Stubbings et al., 2015).

Emotional tone scores (bottom right panel) were the most evenly distributed of the four LIWC summary variables. Higher scores (> 50) reflect more positive emotional tone (Cohn, Mehl, & Pennebaker, 2004). Participants spanned the full range of the scale, and the mean was 57 indicating a neutral-to-positive emotional tone. There was a gradual rise in the number of scores towards the negative end of the scale, indicating that the sample contained individuals experiencing severe negative emotions. Encouragingly, there was also a sharp spike in the most positive interval of the scale (90–99), indicating that many participants were using positive emotion words, which included positive feelings or expressions of gratitude to the therapist.

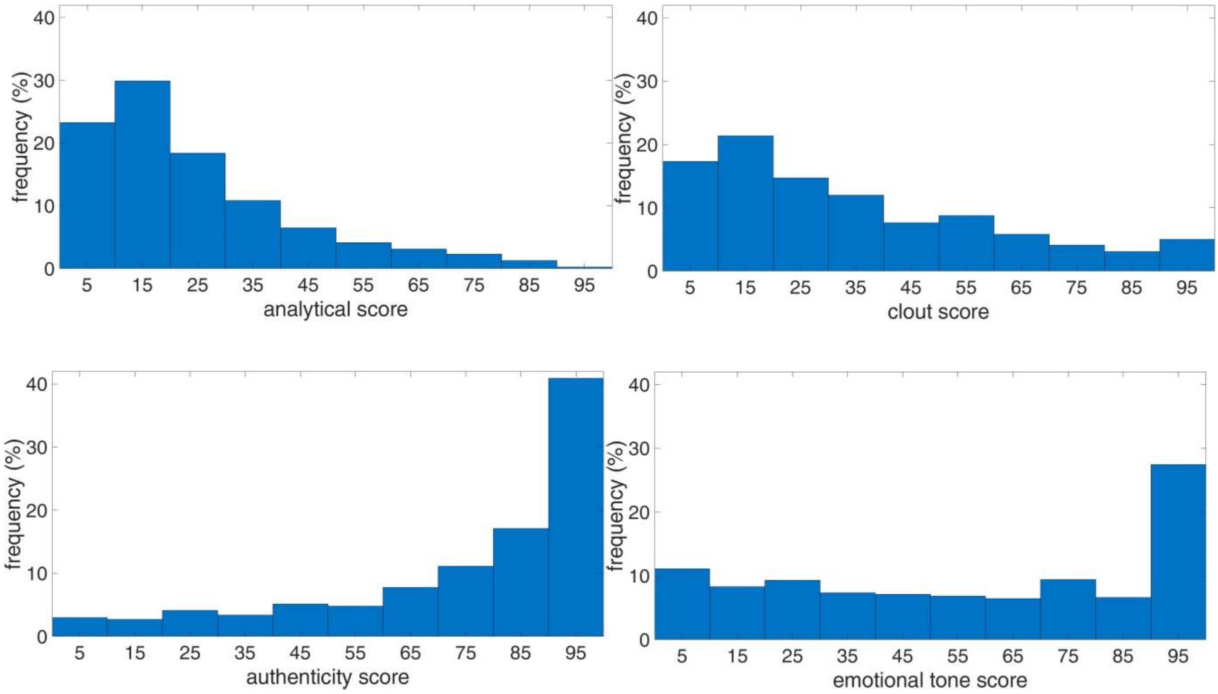

Figure 8. LIWC scores for the basic dimensions analytical (top left), clout (top right), authenticity (bottom left), and emotional tone (bottom right).

The category with the best-established relationship to mental health is that of first-person singular pronouns. Overuse of first-person singular pronouns (e.g., *I, me, my, mine*) is a marker of depression (Fast & Funder, 2010; Pyszczynski & Greenberg, 1987; Weintraub, 1981), and predicts severity of depressive symptoms 8 months after treatment (Zimmermann et al., 2017), although recent findings suggest that first-person singular pronoun use may be indicative of a general proneness to distress or negative emotions rather than of depression specifically (Lyons et al., 2018; Tackman et al., 2019). As shown in Table 3, use of first-person singular pronouns comprised 10% of words.

Table 3. Percentage of words falling within the LIWC categories first-person singular pronouns, positive emotion, negative emotion, causation, discrepancy, insight and social processes.

Indicators	Mean	Median	Min	Max
First-person singular pronouns	10.0	10.3	0.0	22.5
Positive emotion	5.3	4.4	0.0	27.8
Negative emotion	2.7	2.6	0.0	10.1
Causation	1.6	1.6	0.0	6.5
Insight	2.8	2.8	0.0	10.3
Discrepancy	2.0	1.8	0.0	12.5
Social processes	10.2	9.5	0.0	35.3

Social process words (e.g., *share*, *we*) also comprised approximately 10% of the words within a session. This is to be expected, as the participants were reflecting on their relationships with others.

Use of positive (e.g., *happy*, *brave*) and negative (e.g., *sad*, *desperate*) emotion words are known to relate to mental health and symptom severity. Individuals with depression use more negative and fewer positive emotion words (Molendijk et al., 2010; Rude et al., 2004). Reduced use of negative emotion words predicts symptom improvement (Arntz et al., 2012). At present, the frequency of positive emotion words shows a positive skew (Figure 9, top right panel), as might be expected for individuals undergoing psychological counselling.

There is some evidence that the use of absolutist words (i.e., words that indicate certainty such as *always*, *totally*, *constantly*, *forever*, *completely*, *entire*) may predict suicide ideation better than negative emotion words or first-person pronouns (Al-Mosaiwi & Johnstone, 2018; Fekete,

2002). As shown in Figure 9, second-from-top right panel, the distributions of causation words (e.g., *because*, *aggravate*, *basis*) resemble that of the negative emotion and insight categories. The distribution of discrepancy words (e.g., *wouldn't*, *unusual*, *abnormal, impossible*) shown in Figure 9, bottom right panel, is somewhat more positively skewed, which suggests that there is considerable variability within the data concerning the severity of mental health issues being experienced by participants. We expect those participants experiencing greater psychological distress to make greater use of causation words (Arntz et al., 2012; Dirkse et al., 2015) and less use of discrepancy words (Van der Zanden et al., 2014). In the course of conducting these linguistic analyses, additional outputs from LIWC were generated, and for completeness these are included in Appendix C.

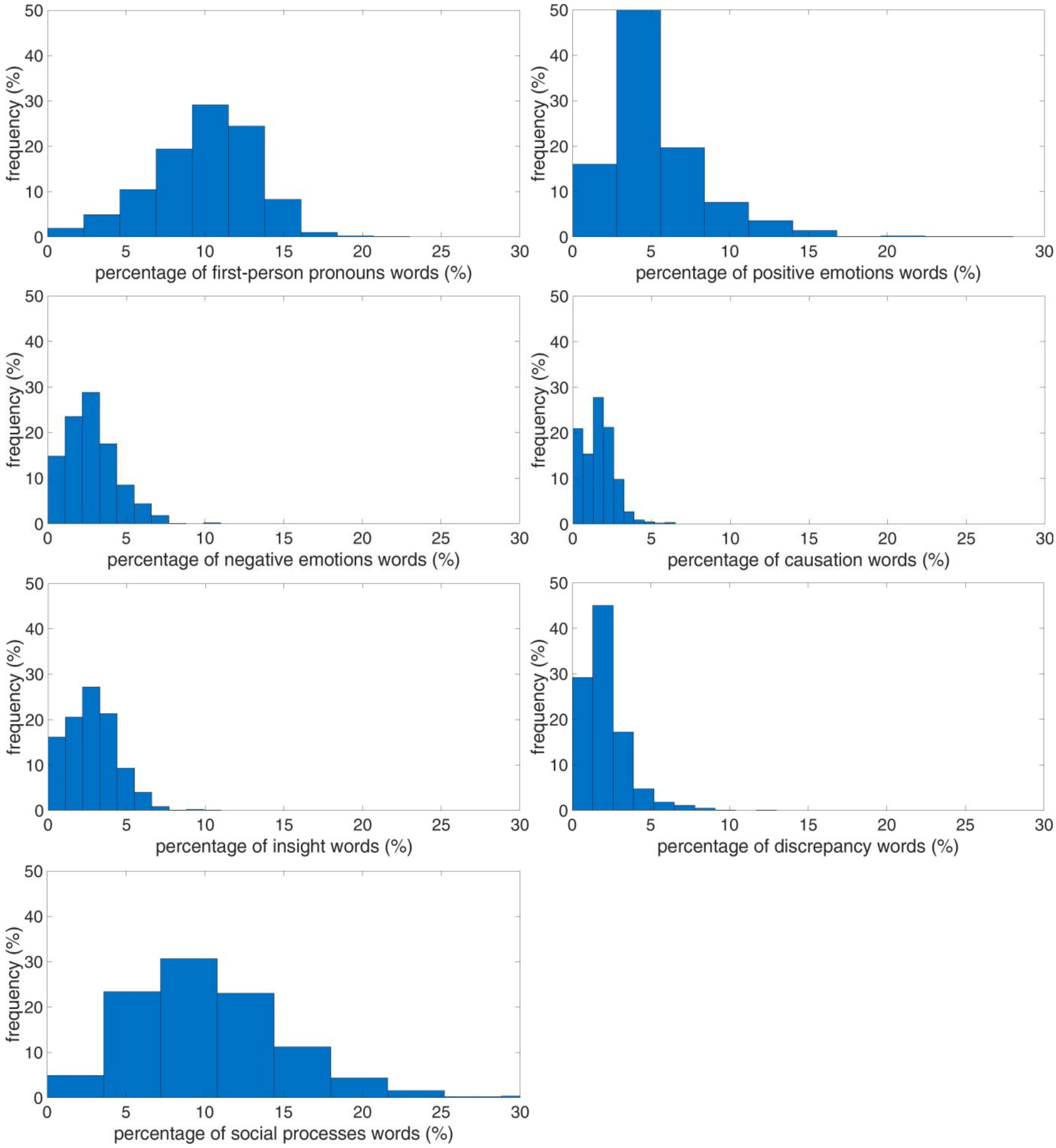

Figure 9. Percentage of words per session for the LIWC categories. First person singular pronouns (top left), positive emotion words (top right), negative emotion words (second-from-top left), causation words (second-from-top right), insight words (second-from-bottom left), discrepancy words (bottom right), and social processes (bottom left).

Predictive Analysis

Discriminant analyses were conducted to explore the relationship between the linguistic categories provided by LIWC and mental health status. Each discriminant model uses a different combination of linguistic categories as predictors to calculate the probabilities of classification response, then outputs the predicated classification label based on highest probability. Then 5-fold cross validation was applied to each of the discriminant models. The performance of the different models was compared to determine which discriminant model performed optimally. Model performance was assessed using three metrics:

1) examining the Area under the Receiver Operating Characteristic curve (AUC). Note that interpretation of AUC varies across disciplines. In applied psychology, given the large number of variables that can influence human behaviour, AUC values equal to or greater than .71 are considered strong effects (Rice & Harris, 2005);

2) general prediction accuracy; and

3) average prediction accuracy when the prediction probability was set to 70%, 80% and 90% (calculated from the accuracy curve, see example shown in Figure 10).

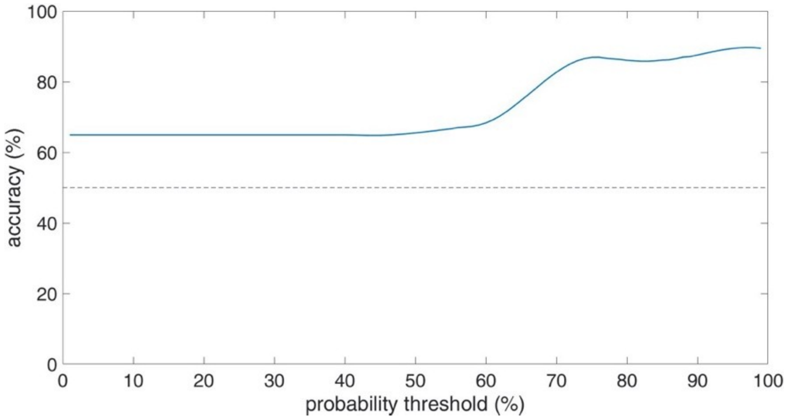

Figure 10. Example of an accuracy curve showing prediction accuracy when the prediction probability is set at different thresholds. The dashed line shows the accuracy at chance level (50% for binary classification).

Binary classification of mental health presenting problem

We first examined whether language use patterns could be used to discriminate the top three presenting problems (i.e., anxiety, depression, stress, see Table 1) from the remaining pool of presenting problems (binary classification). This distinction was deemed important because these three presenting problems were the most frequently occurring within the dataset, and they are the most studied in the literature. Accurate, scalable classification would be useful for screening and for targeted interventions.

Before reporting the binary classification results, let us inspect the differences in LIWC counts between the top three presenting problems and the pool of remaining presenting problems. To do this, we present boxplots for each LIWC count of interest. Boxplots are a standardised way of visualising the distribution of data by presenting the median, the first and third quartiles (edges of the box), and the minimum and maximum (error bars); boxplots indicate the spread of the data, whether it is symmetrical, how tightly it is grouped, and skewness. Differences in boxplots between classification options would be indicative of accurate predictions in the corresponding discriminant analyses. Figure 11 shows boxplots of the four basic LIWC counts. The top three presenting problems, relative to the others, appear to be differentiated by lower clout and authenticity scores, and higher emotional tone scores.

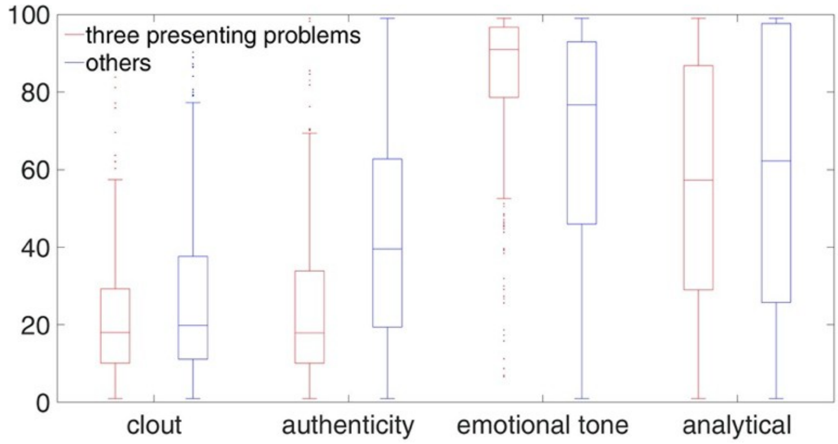

Figure 11. Boxplots of the four basic LIWC counts (clout, authenticity, emotional tone, analytical) for the top three presenting problems (red) and the remaining pool of other presenting problems (blue).

Figure 12 shows boxplots for the LIWC categories. Looking first at the upper panel, the top three presenting problems appear to be differentiated from the others by an increased use of first-person singular pronouns and insight words, but less use of discrepancy and social process words. Turning now to the lower panel, the two classifications may also be differentiated by words in the 'cognitive processes', 'focus future', and 'drives' categories.

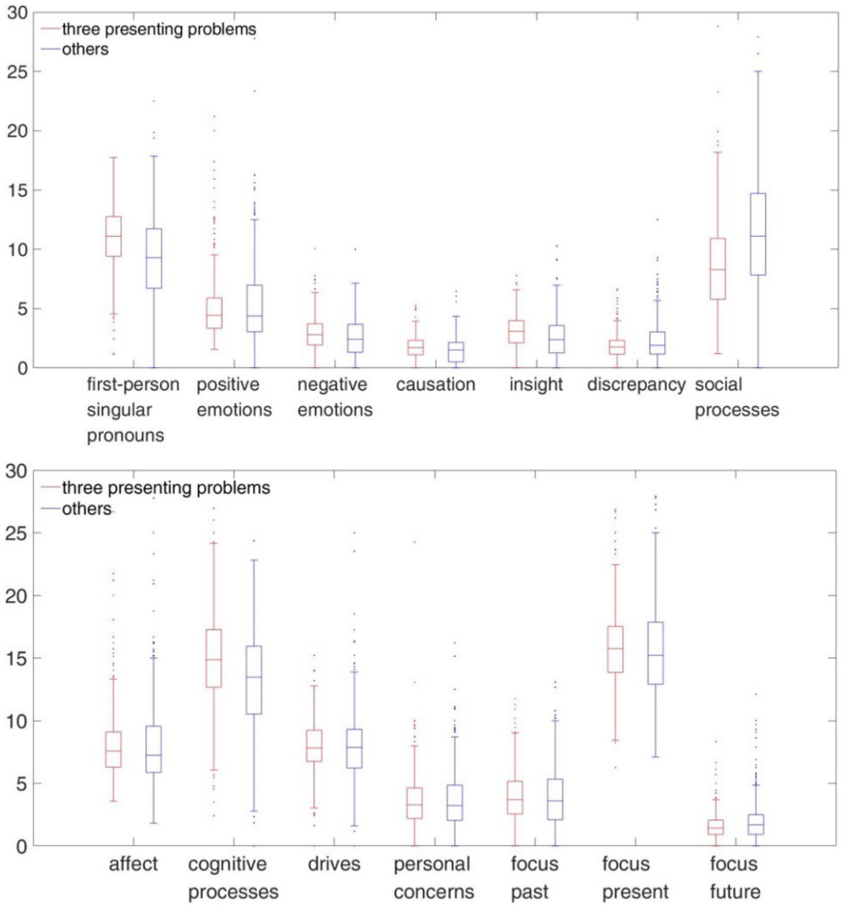

Figure 12. Boxplots of the LIWC categories for the top three presenting problems (red) and the remaining pool of other presenting problems (blue).

Table 4 presents the evaluation metrics (AUC, general accuracy, average accuracy) for each discriminant model (binary classification). The table shows that general accuracy of the best discriminant models reached about 70% (comfortably exceeding the 50% chance level), with area under the receiver operating characteristic curve (AUC) 0.76, indicating good discrimination and a strong effect. When the confidence of prediction is high, the average accuracy of prediction reached about 80%. Interestingly, increasing the number of predictors in the discriminant models did not offer continuous improvements in any of the evaluation metrics. For simplicity, models with three to four predictors seem to be optimal. In terms of LIWC categories, clout, focus future, discrepancy, emotional tones, drives, social processes, insight and first-person singular pronouns are the most frequently occurring predictors among the discriminant models listed in Table 4.

Table 4. Best 5 models for discriminating the top three from the remaining pool of presenting problems. AUC is the area under the receiver operating characteristic curve. Average accuracy is the average accuracy when the predicted probability threshold is set to 70%, 80% and 90%.

Number of predictors	Predictor names	AUC	General accuracy (%)	Average accuracy (%)
n = 1	clout score	0.70	64.9	86
	social processes	0.68	62.2	84.2
	authenticity score	0.66	61.4	81.5
	first-person singular pronouns	0.66	62.7	84
	word count	0.64	56.8	NA
n = 2	clout score + discrepancy	0.74	66.9	80.4
	clout score + functional	0.73	67.3	82.5
	clout score + focus future	0.73	67.0	81.0
	clout score + drives	0.73	66.0	82.9
	clout score + insight	0.73	68.2	83.6
n = 3	clout score + discrepancy + focus future	0.75	67.1	77.6
	clout score + drives + focus future	0.75	67.8	79.4
	insight + social processes + functional	0.74	67.8	81.8
	clout score + authenticity score + focus future	0.74	67	78.0
	clout score + insight + drives	0.74	68.3	81.5
n = 4	clout score + positive emotions + discrepancy + focus future	0.76	67.9	77.7
	clout score + emotional tone score + discrepancy + focus future	0.76	66.9	78.6
	first-person singular pronouns + discrepancy + social processes + focus future	0.75	67.7	77.4
	clout + first-person singular pronouns + discrepancy + focus future	0.75	68.3	77.8
	clout + insight + drives + focus future	0.75	68.4	79.1
n = 5	clout score + emotional tone score + discrepancy + functional + focus future	0.76	68.8	76.5
	clout score + emotional tone score + discrepancy + drives + focus future	0.76	67	77.3
	clout score + emotional tone score + discrepancy + social processes + focus future	0.76	68.4	77.9
	clout score + emotional tone score + insight + discrepancy + focus future	0.76	68.3	77.8
	word count + clout score + emotional tone score + discrepancy + focus future	0.76	67.7	78.5
…	…	…	…	…
n = 21	all predictors	0.72	63.8	67.9

Multiclass classification of presenting problem

The second set of results relates to the task of using language patterns to differentiate between the top three mental health presenting problems (i.e., anxiety, depression, or stress). For this multiclass classification, chance level is 33.3%.

Figure 13 shows boxplots of the four basic LIWC counts. For all four counts, there is considerable overlap across the three presenting problems. Of the four, analytical score appears to be the most promising for differentiating anxiety from depression and stress (red lower than black and blue).

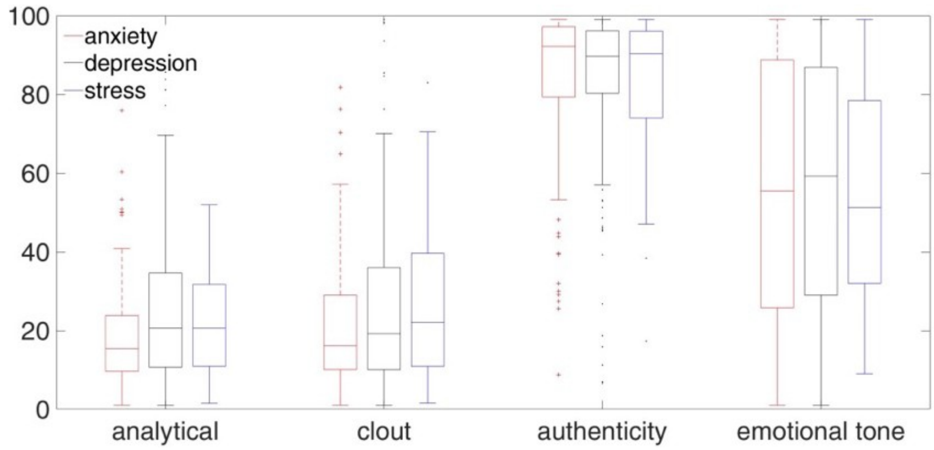

Figure 13. Boxplots of the four basic LIWC counts (analytical, clout, authenticity, emotional tone) for the top three presenting problems: anxiety (red), depression (black), and stress (blue).

Figure 14 shows individual boxplots of the LIWC categories for each of the top three presenting problems. Again, there is considerable overlap across the top three presenting problems, suggesting that they share common features. Of the available LIWC categories, the most promising in terms of differentiation would appear to be first-person singular pronouns, which shows elevated counts for anxiety and depression relative to stress. However, the high degree of overlap across the LIWC categories suggests that it may be difficult to differentiate the top three presenting problems from one another.

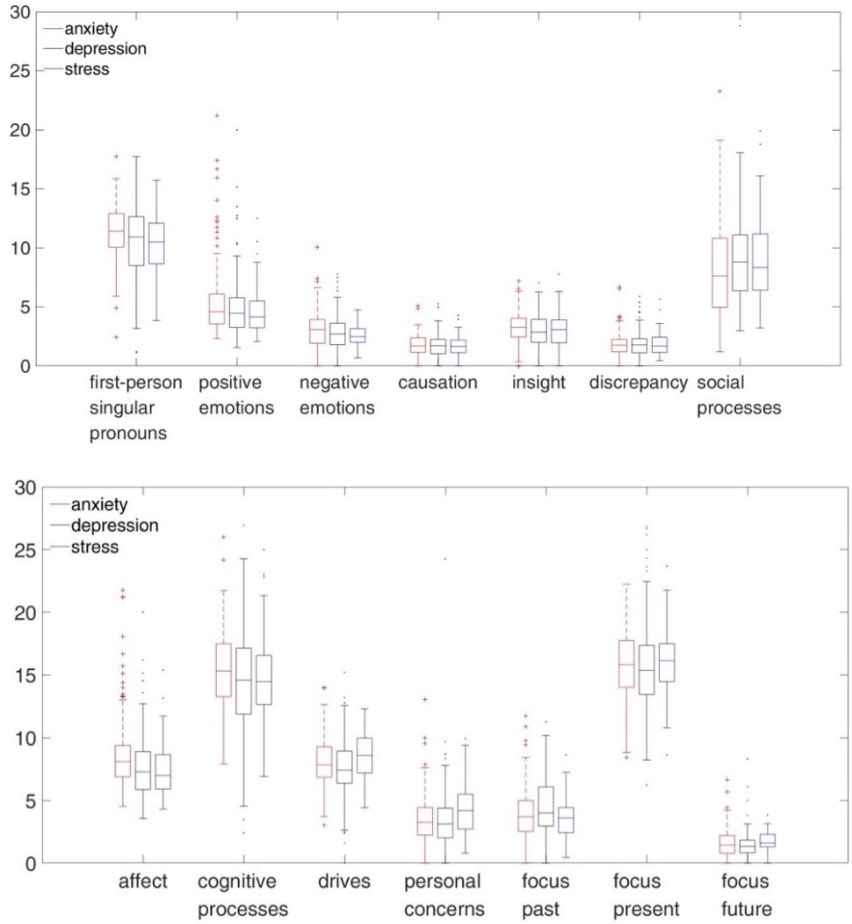

Figure 14. Boxplots of the LIWC categories for each of the top three presenting problems: anxiety (red), depression (black), and stress (blue).

Table 5 presents the evaluation metrics for each model. The table shows that the general accuracy of the best discriminant models was slightly above 50% (compared with 33.3% chance level). Cohen's kappa coefficient reached 0.21, showing fair agreement between prediction and ground truth. When the confidence of prediction is high, the average accuracy of prediction for most of the discriminant models falls between 50–70%. Increasing the number of predictors does not substantially improve prediction accuracy. These results suggest that it is difficult to differentiate the top three presenting problems (i.e., anxiety, depression and stress) on the basis of LIWC categories, although performance is well above chance level. Of the LIWC categories, analytical score, cognitive processes, first-person singular pronouns, focus past and focus present are the most frequently occurring predictors among the discriminant models listed in Table 5.

Table 5. Best 5 discriminant models for differentiating between the top three mental health presenting problems (anxiety, depression, stress).

Number of predictors	Predictor names	Kappa coefficient	General accuracy (%)	Average accuracy (%)
n = 1	analytical score	0.12	49.2	71.6
	cognitive processes	0.12	49.2	52.6
	affect	0.12	48.6	33.3
	first-person singular pronouns	0.09	47.2	83.3
	social processes	0.09	46.9	0
n = 2	analytical score + first-person singular pronouns	0.14	50.3	75.1
	analytical score + focus past	0.14	50.3	74.2
	analytical score + cognitive processes	0.14	50	70.6
	first-person singular pronouns + cognitive processes	0.14	50	54.2
	first-person singular pronouns + focus past	0.14	50	57.1
n = 3	first-person singular pronouns + negative emotions + functional	0.18	50.6	66.8
	analytical score + focus past + focus present	0.17	52	71.7
	analytical score + emotional tone score + drives	0.17	51.4	77.5
	emotional tone score + cognitive processes + drives	0.17	51.4	66.7
	first-person singular pronouns + cognitive processes + focus present	0.17	51.4	56.2
n = 4	negative emotions + social processes + functional + focus present	0.21	50.8	68.7
	negative emotions + affect + drives + focus past	0.21	48.9	60.6
	analytical score + affect + cognitive processes + focus present	0.2	52	64.6
	word count + analytical score + causation + focus past	0.19	52	66.1
	word count + analytical score + causation + focus present	0.19	52	62.7
...	...	...	...	...
n = 21	all predictors	0.09	43.3	46.3

Binary classification of self-rating of mental well-being

The next set of analyses concerns whether language use patterns can identify individuals with the poorest future mental health status by discriminating those cases that rated their health as "poor" from the rest, that is, those who assigned the ratings "fair" through "excellent" (binary classification). Again, this distinction is important because those participants who rated their mental health as "poor" are more likely to require targeted intervention. Boxplots of each LIWC category broken down by those who rated their mental health as poor versus fair- excellent are presented in Appendix D.

Table 6 presents the evaluation metrics for each model. The table shows that the general accuracy of the best discriminant models reached about 80% (far exceeding the 50% chance level), with the area under the receiver operating characteristic curve (AUC) reaching 0.73, showing good discrimination. When the confidence of prediction is high, the average accuracy of prediction falls within the range of 80–90%. Increasing the number of predictors does not substantially improve AUC and prediction accuracy. For simplicity, models with four to five predictors seem to be optimal. Analytical score, positive emotions, discrepancy, causation, drives, first-person singular pronouns and cognitive processes are the most frequently occurring predictors among the best performing discriminant models.

Table 6. Best 5 discriminant models for discriminating "poor" response to self-rated mental health from other ratings (fair – excellent).

Number of predictors	Predictor names	AUC	General accuracy (%)	Average accuracy (%)
n = 1	analytical score	0.59	79.4	84.3
	discrepancy	0.59	79.4	82.7
	insight	0.53	77.6	53.5
	focus present	0.51	79.4	75.9
	causation	0.5	79.4	82
n = 2	analytical score + other	0.66	79.4	88.4
	discrepancy + drives	0.64	79.4	87.2
	clout score + social processes	0.63	79.4	87.2
	analytical score + emotional tone score	0.62	79.4	85.9
	analytical score + positive emotions	0.62	79.4	85.8
n = 3	positive emotions + discrepancy + personal concerns	0.7	81.2	89
	analytical score + other + drives	0.69	79.4	86.5
	analytical score + clout score + other	0.68	76.4	88.8
	analytical score + positive emotions + other	0.67	79.4	86.1
	analytical score + positive emotions + discrepancy	0.66	80	88.6
n = 4	analytical score + other + cognitive processes + drives	0.72	78.2	87.5
	analytical score + positive emotions + discrepancy + personal concerns	0.71	78.2	89.2
	positive emotions + causation + discrepancy + personal concerns	0.7	77.6	90
	analytical score + clout score + first-person pronouns + positive emotions	0.7	80	88.8
	analytical score + positive emotions + discrepancy + drives	0.7	78.2	87.6
n = 5	analytical score + positive emotions + causation + discrepancy + drives	0.73	80.6	87.9
	analytical score + clout score + positive emotions + social processes + other	0.72	80	88
	analytical score + emotional tone score + discrepancy + other + personal concerns	0.72	78.8	87.9
	analytical score + positive emotions + discrepancy + other + drives	0.72	80	87.5
	clout score + positive emotions + discrepancy + social processes + personal concerns	0.72	81.2	89.7
…	…	…	…	…
n = 21	all predictors	0.45	34.7	32.1

A subset of participants (*n* = 49) responded to the single-item mental health self-rating immediately following treatment. On the basis of language use patterns, a binary classification procedure was able to distinguish those who rated their current mental health status as "poor" from those who rated their health as "fair" to "excellent" (2-5 out of 5) with high discrimination accuracy (AUC 0.95, general accuracy 85.7% and average accuracy 88.7%).

All participants who had engaged in the text-based counselling service since August 2019 were contacted in July 2020 and asked to respond to the single-item rating of their mental health. This increased the number of responses from 49 to 165. Binary classification of this expanded data set yielded an acceptable accuracy rate (AUC 0.73), although this was not as high as for the clients who rated their mental health immediately after counselling had occurred. A caveat is that these 116 additional respondents rated their mental health at the same time point, and this was weeks and in some instances months (up to 10 months later) after having participated in counselling (see Appendix E). We interpret this as an encouraging indication that language use patterns are robust predictors of mental health status, and that a larger data set of mental health ratings recorded immediately after counselling would likely yield excellent classification based on language use patterns. All analyses were rerun with the custom Australianised dictionary, but this did not improve the accuracy for any of the models (Appendix F).

Discussion

Principal Findings

This study sought to determine whether language use patterns during the course of text-based counselling with a human therapist could be used to predict mental status. Text-based counselling is effective in improving psychological wellbeing and mental health (Cohen & Kerr, 1999; DellaCrosse, Mahan, & Hull, 2019; Fukkink & Hermanns, 2009a, 2009b; Kramer, Conijn, Oijevaar, & Riper, 2014). Here, computational linguistic techniques were used to explore predictive relationships between language use patterns and the participants' underlying psychological presenting problem which was recorded prior to the commencement of counselling, as well as their self-ratings of their current mental health status which were recorded after counselling had concluded. The results showed that the computational analysis was able to predict the top three presenting problems (anxiety, depression, and stress) with an accuracy of 80% (see Table 4). The analysis was able to discriminate between those top three presenting problems with an accuracy ranging from 50-70% (see Table 5), which was above chance level. For the prediction of mental health status as determined by responses to the question "*How would you rate your mental health now?"*, the average accuracy of prediction was good, ranging from 80–90% (see Table 6).

Language use patterns can be used to accurately classify presenting problem and future mental health status

The findings suggest that language use patterns are indeed useful indicators of mental health presenting problems and are also predictive of future mental health status. We were able to use linguistic patterns to discriminate the top three presenting problems from the remaining pool of 17 presenting problems. This binary classification was able to separate participants with high accuracy. This finding is consistent with previous studies that have reported that depression has linguistic markers, such as increased use of first person personal pronouns (Fast & Funder, 2010; Molendijk et al., 2010; Pyszczynski & Greenberg, 1987; Rude et al., 2004; Weintraub, 1981) and negative emotion words (Arntz et al., 2012). The present work extends past findings by examining language use in a sample of participants with clinically significant presentation, who were receiving text-based counselling. Additionally, the approach used here confirms the viability of using text-based counselling transcripts to enable computational linguistic analyses to determine the type of presenting problem.

The predictive analysis was successful in classifying the participants based on their self-ratings of their mental health. Binary classification yielded high accuracy in identifying those participants who went on to rate their mental health as "poor" following counselling versus those who rated it as "fair" to "excellent". This finding provides compelling evidence that linguistic patterns are accurate and robust predictors of future mental health status. The results support studies that have shown that there are linguistic markers related to reductions in symptom severity and improved treatment outcomes (Arntz et al., 2012; Huston et al., 2019; Van der Zanden et al., 2014).

To improve accuracy further, we recommend measuring participants' mental health in a standardised way so as to reduce variability introduced, for example, by differences in how long after the completion of counselling mental health status was measured, although we acknowledge the difficulties in implementing these recommendations in a real-world clinical context.

Unlike Seabrook et al. (2018), use of a customised dictionary did not improve the accuracy of our analyses. It is unclear why we did not observe similar improvements in depression identification as reported by those authors. There are several important differences between the two studies concerning the participant populations and methods of data collection. Seabrook and colleagues recruited from a younger age range, likely from urban areas, and analysed Facebook and Twitter status updates and related these to scores from a mood-tracking app that their participants downloaded and used. This differs markedly from the farmers recruited here, who were engaged in text-based psychological counselling. It is possible that the counselling context is less likely to elicit Australianisms, such as slang and other colloquialisms, than posts on social media.

Differentiating anxiety from depression from stress is difficult

The observation that the models successfully differentiated the top three presenting problems from the rest but were less accurate in differentiating between the top three presenting problems requires explanation. It appears to suggest that the top three presenting problems (anxiety, depression, stress) share common features; this commonality may refer to both the linguistic patterns that individuals with these conditions make use of, as well as the psychological symptoms that they exhibit. For instance, all are likely to affect mood and motivation. Depression and anxiety are known to be highly comorbid conditions. Indeed, 45.7% of individuals with lifetime major depressive disorder also had a lifetime history of one or more anxiety disorder (Kessler et al., 2015). Depression and anxiety also commonly coexist during the same time frame (Kessler et al., 1994). Further, stress is a response to pressures or threats, while anxiety may manifest as a reaction to the stress. Anxiety may have no clear cause, and as a result last longer and be more difficult to treat, but at the time of presentation both may be affecting the individual. Recall that our participants were recruited during the combined unprecedented events of the Australian bushfire season of 2019-2020 and the COVID-19 global pandemic. It seems entirely valid that it may not be possible to statistically differentiate anxiety, depression, and stress from one another because a sizeable proportion of participants may have been co-presenting with two or all three of these mental health problems simultaneously. Another explanation is that it is simply unknown if these conditions can be differentiated using default LIWC categories. This is the first study to attempt to differentiate depression from anxiety from stress using linguistic patterns as computed by LIWC. It may be possible to improve differentiation by refining the analysis to count the words with the strongest predictive power to separate one condition from the other (i.e., going to a finer level of resolution than the coarse LIWC category) as has been demonstrated elsewhere (Owen et al., 2005). These possibilities await to be tested in future research.

Implications for practice

The potential applications of an accurate, scalable approach to mental health are far-reaching, with implications for early screening and targeted interventions. Mental disorders are a leading cause of disability worldwide with enormous economic consequences, including lost productivity and employee absenteeism (McTernan, Dollard, & LaMontagne, 2013), and additional strain placed on carers (Briggs & Fisher, 2000) and health systems (Lee et al., 2017). The economic costs due to lost productivity and absenteeism, even in the case of mild depression, are estimated to be $8 billion per annum (e.g., McTernan et al., 2013). Although natural language processing of electronic health records is increasingly being used to study mental illness (Edgcomb & Zima, 2019), case notes written by therapists and clinicians do not capture the implicit nuances present in the language use patterns of their clients. Thus, they do not lend themselves to the types of predictive analyses described here. Being able to predict future mental health status would enable proactive and early identification of at-risk individuals and bolster harm minimisation efforts. The ultimate goal of such research is to accurately predict which individuals are at risk of mental health problems (including suicide) so that mental health professionals can intervene and save that person's life. The present data offer the tantalising possibility that text-based predictors of mental health status may enable large-scale automatic screening of mental illness and identification of at-risk individuals in the not too distant future.

Limitations and future directions

There are several limitations to this study. First, language use patterns were related to the participants' presenting problems and self-rated mental health status, but no neuropsychological assessments were administered. Given that our ultimate aim is to identify individuals at-risk of clinically significant presentation, it would be advantageous to be able to relate language use patterns to standardised measures of psychological function.

Second, although three quarters of participants completed multiple sessions of counselling, the data set only permitted us to relate their language use patterns to presenting problems (recorded prior to the commencement of treatment) or self-reported mental health status (recorded after they had received counselling). Given that changes in language use have been observed during the course of treatment, and these changes have been linked to treatment outcomes (e.g. Banham & Schweitzer, 2015; Bento, Ribeiro, Salgado, Mendes, & Gonçalves, 2014; Reyes et al., 2008), it would be useful to track such changes longitudinally when trying to determine a client's presenting problem as well. Additionally, changes in language use could also be predictive of responsiveness to treatment and future mental health status. For example, increasing use of reflexive language and decreasing use of external language in therapeutic conversation has been associated with better therapeutic outcomes (Banham & Schweitzer, 2015).

Third, although the sample analysed was considerable, replication of this approach with a larger data set will increase statistical power and support detection of significant associations between an increased number of variables.

To address these limitations, future studies should include standardised neuropsychological assessments and pharmacological management history. Ideally, these should be administered at multiple time points during the course of the study so as to measure changes in symptom severity and how they are reflected in changes in language use.

Conclusions and recommendations

This study suggests that language use patterns during the course of text-based counselling are robust predictors of mental health status in famers living in rural and remote communities. Linguistic patterns can be used to accurately assign individuals into one of the top three presenting problem categories. They can also differentiate those top three presenting problems from the pool of other presenting problems via binary classification. If replicated in other samples, computational linguistic analyses might be applied to big data approaches for mental health screening at a population level, providing insight into the linguistic patterns underlying the mental health needs of Australians and improving the speed and scale of identification of at-risk individuals. We were also able to accurately predict future mental health status (as measured by self-ratings) based on linguistic patterns. This technique could potentially provide a sensitive measure of future mental health status that may be used as an early indicator of being predisposed to mental health conditions such as depression, anxiety and stress.

Text-based counselling serves an important treatment function and has the potential to span great distances to provide e-mental health services to areas where service capacity is lacking. Although text-based communication has limitations (slower than vocal exchanges, faceless, impersonal), for some segments of the population, it is appealing because of those limits rather than in spite of them (low bandwidth, perceived as offering space and privacy). This study contributes to the understanding of the best approaches for using technology to promote mental well-being and identify individuals at-risk of mental health problems.

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Appendix A: Custom Australianised LIWC dictionary

The dictionary provided with the standard version of LIWC covers a wide range of topics and contains an extensive vocabulary, including familiar usage and slang as well as internet language. To improve the adequacy of the LIWC software to the specific Australian environment, a number of words and expressions were added to these vocabulary lists. In particular, all the lists were spell-checked, and Australian spelling variants were added, as shown in Table A1. Some spelling variants were already taken care of in LIWC (e.g. 'favor/favour'), but not necessarily in all categories. Thus, to permit replicability, the table lists all the instances that were added in each category.

Table A1. Australian spellings added to LIWC.

LIWC Category	Added	Equivalent in LIWC
Verbs (Category 20)	travelled	traveled
	travelling	traveling
Adjectives (Category 21)	crueller	crueler
	cruellest	cruelest
	defenceless	defenseless
	foreseeable	forseeable
	grey	gray
	mouldy	moldy
	unsavoury	unsavory
Comparatives (Category 22)	crueller	crueler
	cruellest	cruelest
Affect (Category 30)	agonise	agonize
	crueller	crueler
	cruellest	cruelest
Posemo (Category 31)	splendour	splendor
Negemo (Category 32)	agonis*	agoniz*
	crueller	crueler
	cruellest	cruelest
	dishonour	dishonor
	unsavoury	unsavory
Anger (Category 34)	crueller	crueler
	cruellest	cruelest
Sad (Category 35)	agonis*	agoniz*
CogProc (Category 50)	sceptic*	skeptic*
Insight (Category 51)	sceptic*	skeptic*

Tentat (Category 54)	sceptic*	skeptic*
Bio (Category 70)	gonorrhoea	gonorrhea
	gynaecolog*	gynecolog*
Health (Category 72)	gonorrhoea	gonorrhea
	gynaecolog*	gynecolog*
	orthopaed*	orthoped*
	paediatr*	pediatr*
Sexual (Category 73)	gonorrhoea	gonorrhea
Drives (Category 80)	actualis*	actualiz*
	defence*	defense*
	dishonour*	dishonor*
	neighbour*	neighbor*
Affiliation (Category 81)	neighbour*	neighbor*
Achieve (Category 82)	actualis*	actualiz*
	fulfil*	fulfill*
Power (Category 83)	defenceless	defenceless
	dishonour	dishonor
Reward (Category 84)	fulfil*	fulfill*
Risk (Category 85)	defence	defense
FocusPast (Category 90)	travelled	traveled
FocusFuture (Category 92)	foreseeable	forseeable
Relativ (Category 100)	travelled	traveled
	traveller*	traveler*
	travelling	traveling
Motion (Category 101)	travelled	traveled
	traveller*	traveler*
	travelling	traveling
Space (Category 102)	kilometre	kilometer
Work (Category 110)	finalis*	finaliz*
Leisure (Category 111)	travelled	traveled
	traveller*	traveler*
	travelling	traveling

In addition, words that are commonly found in the Australian vernacular (e.g. 'youse', 'gonna') were added as shown in Table A2, which also contains the Australian equivalents for some common words (e.g. 'housemate' or 'mobile'), brand names (e.g. 'Panadol'), and some acronyms or proper names for Australian institutions (e.g. 'ATAR', 'ATO', 'Centrelink') as appropriate. In addition, a few terms were added to complete some lists (e.g. 'ex-wife', etc). There would be many more words to add in the Informal (120) and Swear (121) categories, but this was limited to ‘abo’ (cf. ‘nigger’) and ‘ta’.

Table A2. Australian words added to LIWC.

LIWC Category	Added	Equivalent in LIWC
Pronouns (Categories 1, 2, 3, 6)	youse	y'all
AuxVerb (Category 12)	gonna	gunna
Social (Category 40)	ex-wife	
	ex-wives	
	ex-husb*	
	housemate*	[cf. roommate*]
	youse	
Family (Category 41)	ex-wife	
	ex-wives	
	ex-husb*	
Friend (Category 42)	housemate*	[cf. roommate*]
Female (Category 43)	ex-girl*	
	ex-wife	
	ex-wives	
Male (Category 44)	ex-boy*	
	ex-husb*	
Percept (Category 60)	mobile	[cf. cellphone]
Hear (Category 62)	mobile	[cf. cellphone]
Bio (Category 70)	Panadol	[cf. Advil]
	bum	[cf. butt]
	lollies	[cf. candy]
	Paracetamol	[cf. Tylenol]
Health (Category 72)	Panadol	[cf. Advil]
	Paracetamol	[cf. Tylenol]
Ingest (Category 74)	lollies	[cf. candy]
Drives (Category 80)	ATAR	[cf. GPA]
Affiliation (Category 81)	housemate*	[cf. roommate*]
Achieve (Category 82)	ATAR	[cf. GPA]
Power (Category 83)	JP	[cf. judge]
Relativ (Category 100)	housemate*	[cf. roommate*]
Space (Category 102)	housemate*	[cf. roommate*]
Work (Category 110)	ATAR	[cf. GPA]

	Centrelink	[cf. unemployed]
Leisure (Category 111)	footy	[cf. football]
	AFL	
	netball	
Home (Category 112)	housemate*	[cf. roommate*]
	flat	
	unit	
Money (Category 113)	ATO	[cf. IRS]
	ASD	[cf. USD]
Religion (Category 114)	bahai	
	baha'i	
Informal (Category 120)	abo	[cf. nigger]
	ta	[cf. thks]
Swear (Category 121)	abo	[cf. nigger]

Appendix B: Client survey

At the end of each session, the participants were asked to answer a short survey concerning their experience with the *Virtual Psychologist* service. The survey can be found at: https://www.surveymonkey.com/r/WNW5MXN?c=6230.

The survey consisted of a single question for self-rating of mental health on a 5-point scale ranging from "poor" to "excellent" and was presented as shown in the screenshot below.

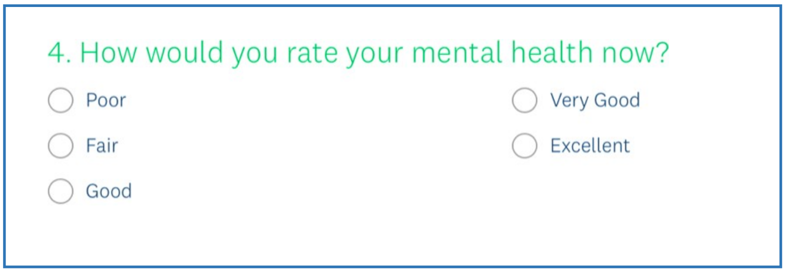


Figure B1. Single-item self-rating of mental health survey, as it was presented to participants.

Appendix C: Other detailed LIWC counts

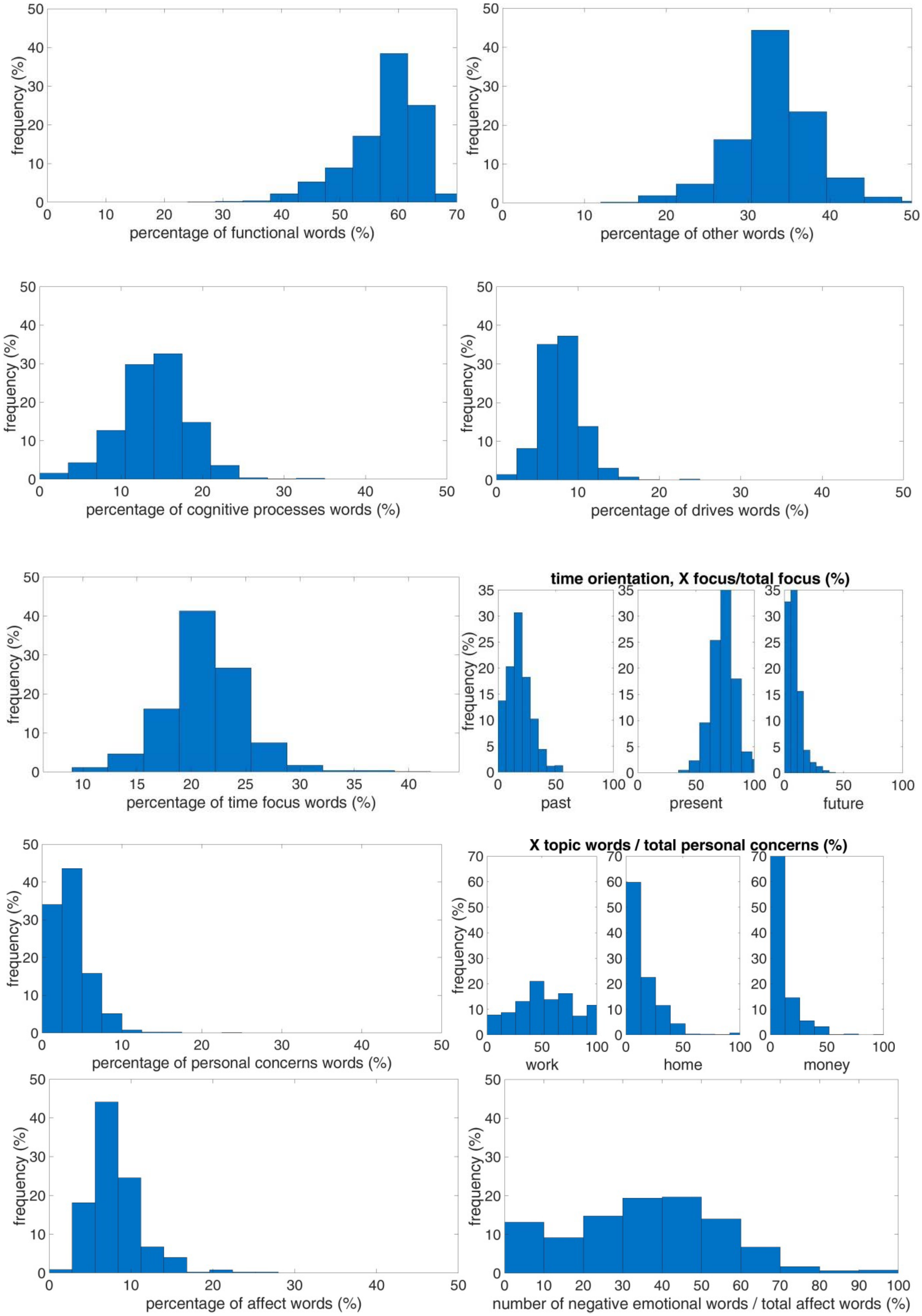
In addition to the counts of interest presented in the Linguistic Analysis, LIWC permits many other detailed counts on the basis of the word categories used as indicators for the basic dimensions discussed. After careful selection, we decided to analyse and report the word counts for the following relevant categories provided by LIWC (Table C1):

- functional words: which include the grammatical categories *pronouns*, *articles*, *prepositions*, *auxiliary verbs*, *adverbs*, *conjunctions*, *negations*
- other grammatical words: including *verbs*, *adjectives*, *comparisons*, *interrogatives*, *numbers*, *quantifiers*
- affect: captures both *positive* and *negative emotional* words
- negative emotional: words related to *anxiety*, *anger*, *sadness*
- cognitive processes: e.g., words related to *insight*, *cause*, *discrepancies*, *tentativeness*, *certainty*, *differentiation*
- drives words: e.g., words related to *affiliation*, *achievement*, *power*, *reward*, *risk*
- time orientation words: e.g., focus on *past*, *present* and *future*

Table C1. Percentage of words falling within the LIWC categories functional words, other words, affect, social, cognitive processes, drives, personal concerns, past focus, present focus, and future focus.

Indicators (%)	Mean	Median	Min	Max
functional words	57.7	59.1	27.5	70.4
other words	33.2	33.3	15.8	57.6
affect	8.1	7.4	1.8	27.8
cognitive processes	14.0	14.2	0.0	34.7
drives	8.0	7.8	0.0	25.0
personal concerns	3.7	3.2	0.0	24.3
past focus	3.9	3.7	0.0	13.1
present focus	15.7	15.5	6.3	31.0
future focus	1.8	1.5	0.0	12.1

Figure C1 provides an overview of words falling within the LIWC categories functional words, other words, affect, social, cognitive processes, drives, personal concerns, past focus, present focus, and future focus. The distributions represent data expressed in terms of percentages of words in each category. (N.B. the horizontal scale of each graph has been adjusted for the purpose of providing the best visualisation of data distribution.)


frequency (%)
percentage of functional words (%)
percentage of other words (%)
percentage of cognitive processes words (%)
percentage of drives words (%)
percentage of time focus words (%)
time orientation, X focus/total focus (%)
past
present
future
percentage of personal concerns words (%)
X topic words / total personal concerns (%)
work
home
money
percentage of affect words (%)
number of negative emotional words / total affect words (%)

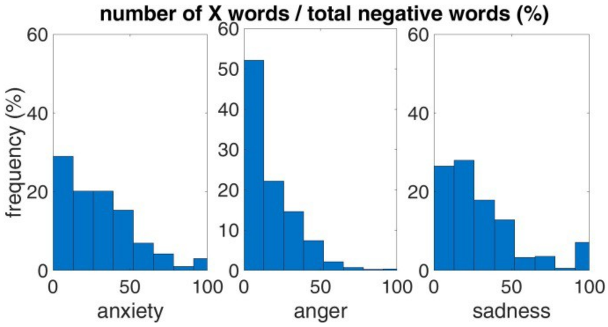
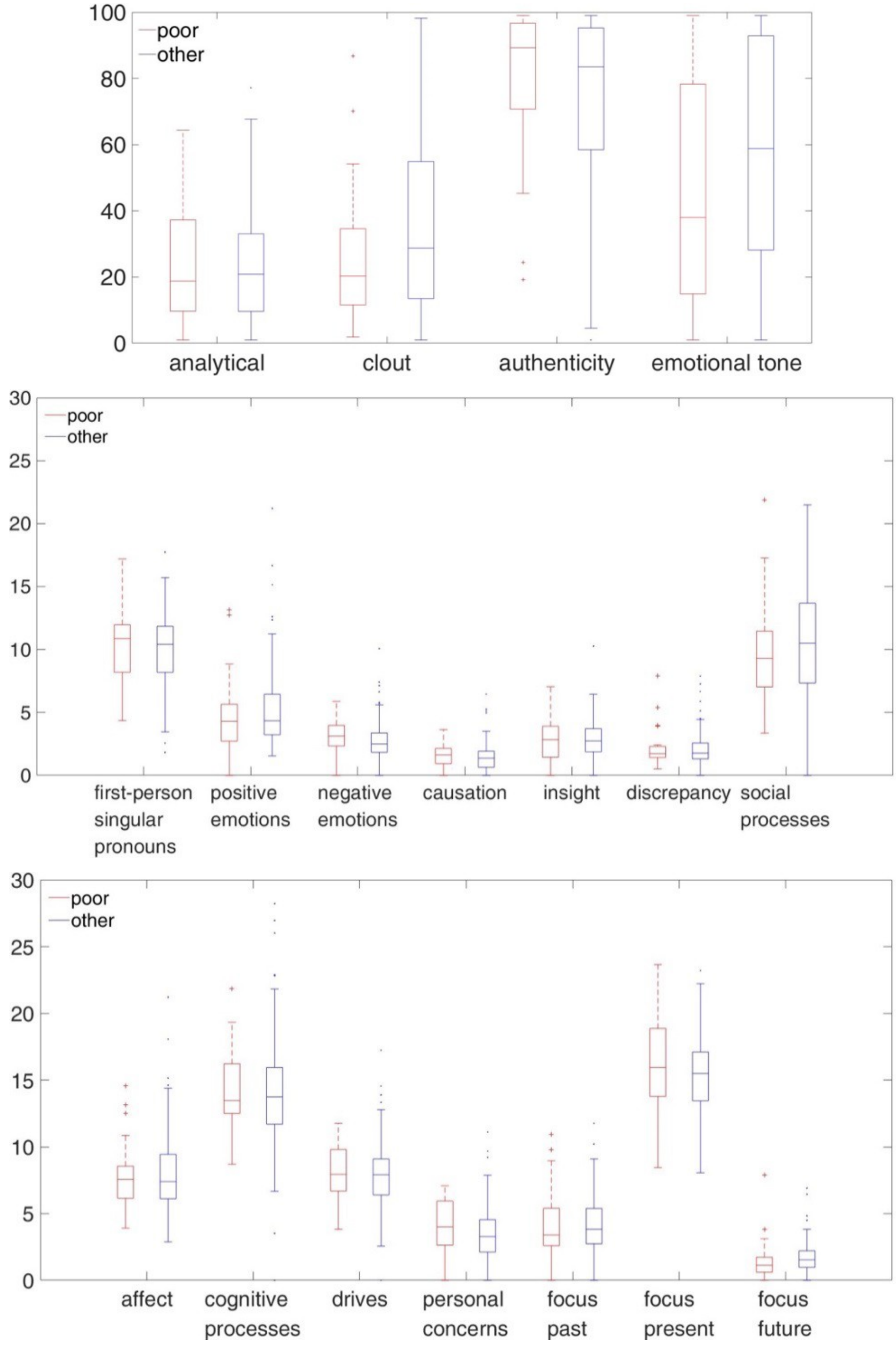


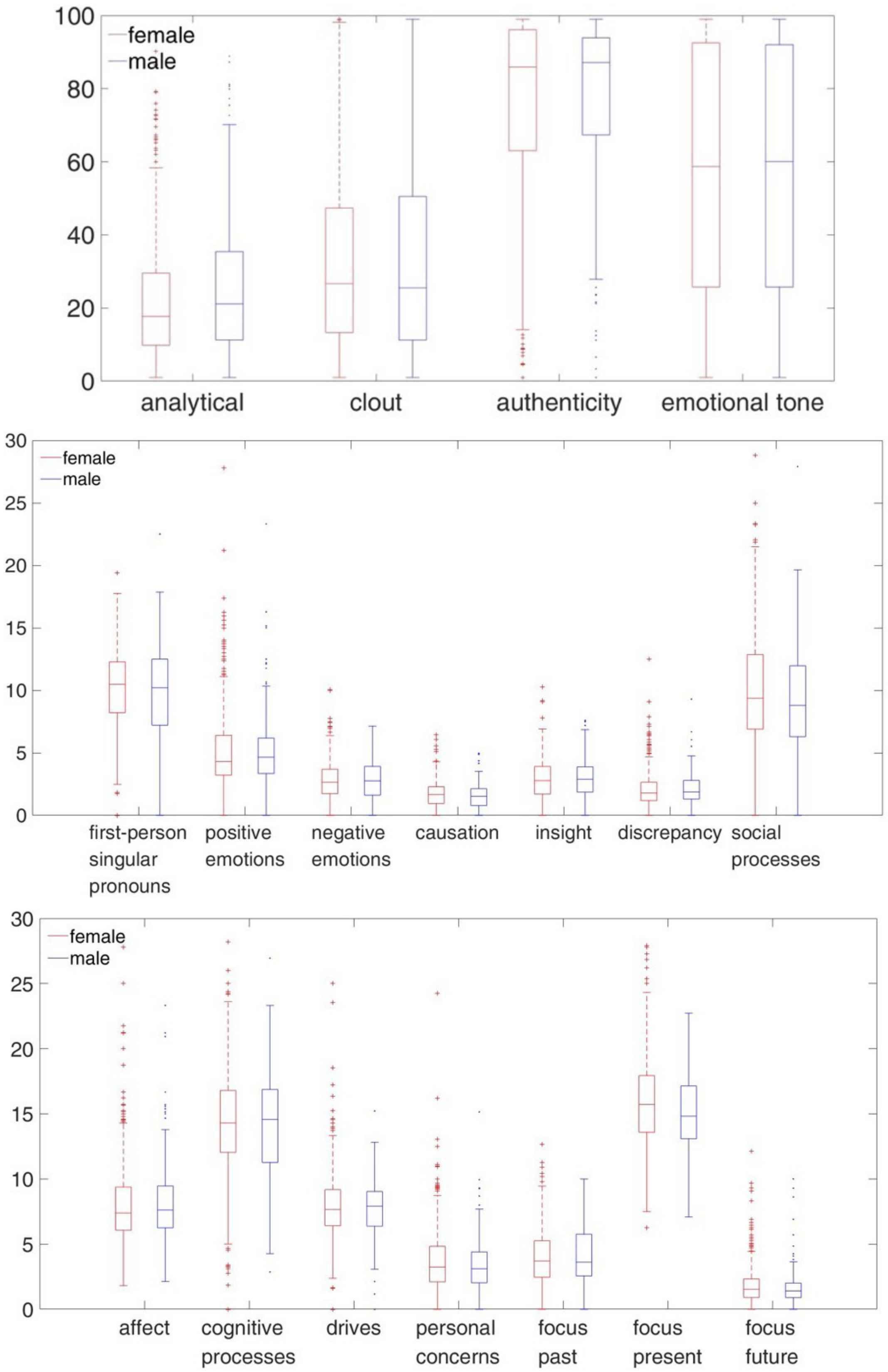
Figure C1. Other detailed counts computed from LIWC.

Appendix D: Boxplots

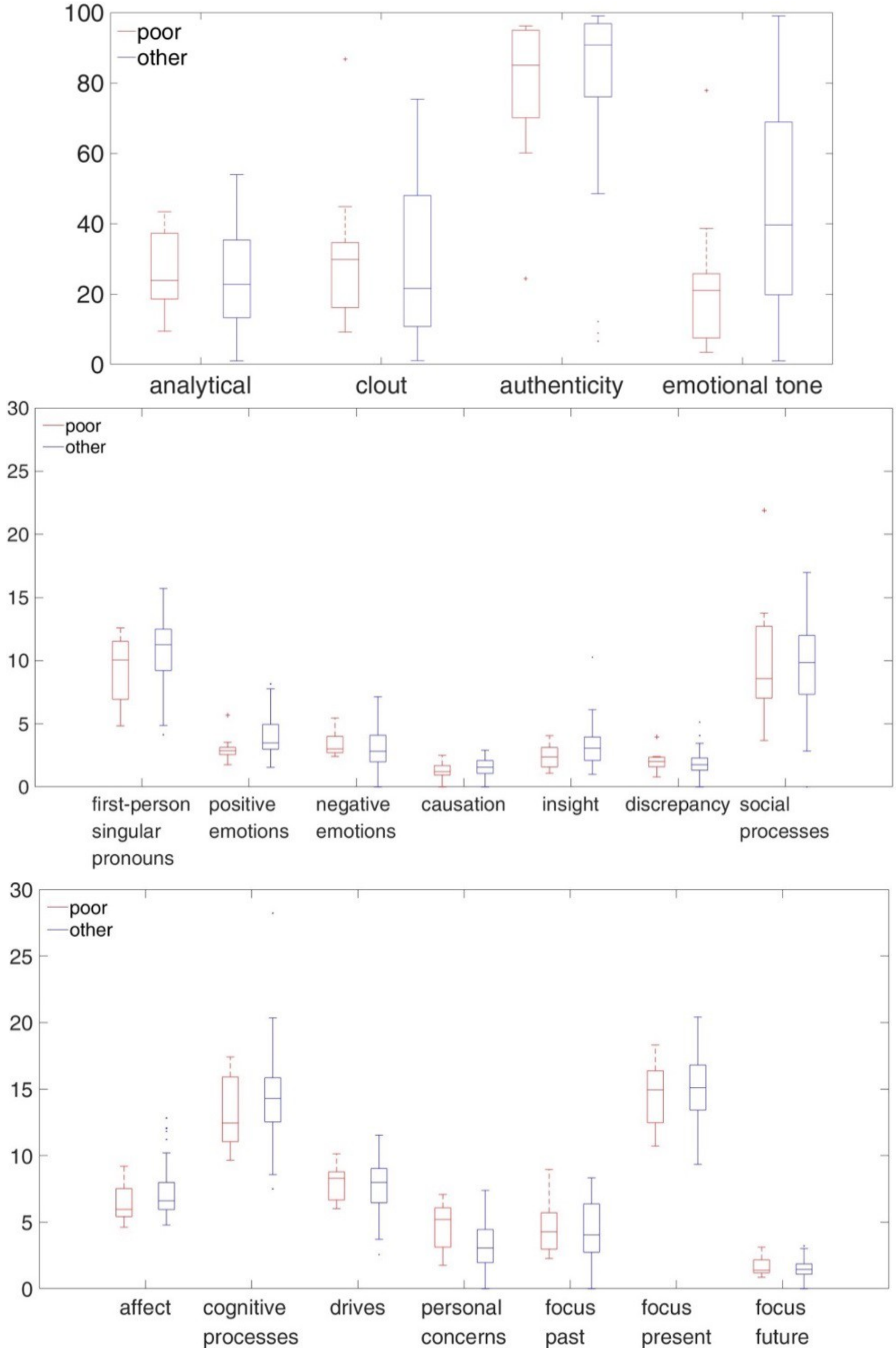
Below are boxplots for each of the LIWC counts for those participants who rated their mental health as “poor” and those who rated it as “fair–excellent”. The two classifications were differentiated with high accuracy using analytical score (top panel), first-person singular pronouns, positive emotions, causation, discrepancy (middle panel), drives, and cognitive processes (bottom panel).



We explored whether LIWC counts could be used to differentiate male from female participants. The results were inconclusive. Our participant sample was biased heavily towards women, but even so, the pattern across variables is remarkably stable across sexes.



As presented in Appendix E, excluding the batch survey data for the self-rating of mental health did not improve the analysis. Here we present boxplots of that self-rating data with the batch survey data excluded for the LIWC counts.



Appendix E: Binary classification of responses to mental health single-item rating with batch survey data excluded

Number of predictors	Predictor names	AUC	General accuracy (%)	Average accuracy (%)
n = 1	functional	0.7	79.6	92.5
	drives	0.68	83.7	82
	analytical score	0.57	79.6	86.1
	first-person singular pronouns	0.56	79.6	85.5
	personal concerns	0.55	79.6	86.2
n = 2	causation + discrepancy	0.82	81.6	95.6
	authenticity score + drives	0.77	81.6	87.8
	functional + drives	0.75	81.6	85.5
	first-person singular pronouns + negative emotions	0.73	75.5	89.7
	negative emotions + functional	0.72	79.6	89.5
n = 3	cognitive processes + drives + focus past	0.83	85.7	89.6
	causation + discrepancy + social processes	0.82	81.6	88.2
	first-person singular pronouns + drives + focus present	0.8	85.7	88.6
	authenticity score + negative emotions + causation	0.78	81.6	90.6
	emotional tone score + first-person singular pronouns + insight	0.77	77.6	87.5
n = 4	word count + positive emotions + functional + focus present	0.95	87.8	92.7
	authenticity score + negative emotions + focus present + focus future	0.92	83.7	88.6
	word count + analytical score + functional + drives	0.91	83.7	87.6
	discrepancy + cognitive processes + drives + focus past	0.88	81.6	90.3
	authenticity score + emotional tone score + affect + focus present	0.86	77.6	90.2
n = 5	word count + analytical score + positive emotions + functional + drives	0.95	85.7	85.5
	word count + positive emotions + functional + focus present + focus future	0.95	85.7	88.7
	word count + emotional tone score + functional + focus present + focus future	0.94	85.7	87.5
	word count + analytical score + social processes + functional + drives	0.93	83.7	86.1
	authenticity score + negative emotions + causation + focus present + focus future	0.92	83.7	89
...	...	...	...	...
n = 21	all predictors	0.45	34.7	32.1

Appendix F: Analyses with custom Australianised dictionary

All analyses were rerun with the custom Australianised dictionary (see Appendix A). Using the customised Australianised dictionary did not improve the accuracy of the models for any of the analyses. Below, we present the model evaluations.

Binary classification of mental health presenting problem: AUC, general accuracy and average accuracy are comparable with those using the built-in dictionary, suggesting that using customised dictionary does not improve the prediction.

Number of predictors	Predictor names	AUC	General accuracy (%)	Average accuracy (%)
n = 1	clout score	0.71	64.8	86
	authenticity score	0.66	61.3	81.7
	word count	0.63	57.7	19
	focus present	0.63	57.3	77.2
	causation	0.63	58	26.9
n = 2	clout score + focus present	0.73	64.8	80.9
	clout score + other	0.73	66.5	84.3
	clout score + focus future	0.72	64.4	78.7
	clout score + social processes	0.72	65.6	81.5
	clout score + insight	0.72	65.2	85.2
n = 3	clout score + insight + focus future	0.74	64.4	78.1
	clout score + other + focus future	0.74	67	77.2
	clout score + authenticity score + focus present	0.74	65.6	77.2
	clout score + other + focus present	0.74	66.8	80.5
	clout score + social processes + other	0.74	66.9	80.5
n = 4	clout score + first-person singular pronouns + social processes + other	0.75	66.9	80.8
	clout score + social processes + other + focus future	0.75	65.8	76
	clout score + emotional tone score + word count + insight	0.75	66.2	84.4
	clout score + social processes + other + focus present	0.75	66.5	79.1
	clout score + first-person singular pronouns + other + focus present	0.74	67.1	80.6
...	...	...	...	...
n = 21	all predictors	0.73	64.8	67.2

Binary classification of self-rating of mental well-being revealed performance comparable with those models using the built-in dictionary, suggesting that using the customised dictionary does not improve predictive accuracy.

Number of predictors	Predictor names	AUC	General accuracy (%)	Average accuracy (%)
n =1	analytical score	0.61	79.4	85.6
	affect	0.58	77.6	54.1
	positive emotions	0.57	79.4	85.8
	social processes	0.56	79.4	85.3
	functional	0.55	79.4	79.5
n = 2	positive emotions + affect	0.63	76.4	83.7
	analytical score + affect	0.63	76.4	83.7
	analytical score + negative emotions	0.62	78.2	86.8
	analytical score + cognitive processes	0.62	79.4	85.6
	other + focus past	0.62	80	82.3
n = 3	other + focus past + focus future	0.68	75.8	88.6
	analytical score + other + focus past	0.67	79.4	84.7
	analytical score + cognitive processes + drives	0.66	80	84.4
	emotional tone score + positive emotions + affect	0.66	77	83.2
	analytical score + positive emotions + drives	0.65	78.8	84.6
n = 4	analytical score + first-person singular pronouns + negative emotions + affect	0.71	78.2	86.6
	positive emotions + causation + social processes + affect	0.7	75.8	85.1
	analytical score + first-person pronouns + other + affect	0.69	76.4	87.7
	analytical score + affect + cognitive processes + drives	0.69	76.4	83.9
	analytical score + other + focus past + focus future	0.69	72.7	87.1
...	...	...	...	...
n = 21	all predictors	0.53	75.2	75.6