Journal of Contextual Behavioral Science 18 (2020) 92–98

Contents lists available at ScienceDirect

Journal of Contextual Behavioral Science

journal homepage: www.elsevier.com/locate/jcbs

Empirical Research

Inflexitext: A program assessing psychological inflexibility in unstructured verbal data

Olga V. Berkout[a,*], Angela J. Cathey[b], Dmytry V. Berkout[c]

[a] Department of Psychology, Texas A&M Corpus Christi, United States
[b] ENSO Group, Behavioral Science in the 21st Century, Dallas, TX, United States
[c] DevCo Consulting, Frederick, MD, United States

ARTICLE INFO

Keywords:
Psychological inflexibility
Natural language processing
Verbal behavior
Digital phenotyping

ABSTRACT

This paper describes the development and initial support for Inflexitext, an automated program identifying psychological inflexibility in unstructured verbal data. Written in Python 3.7, Inflexitext produces a psychological inflexibility score based on patterns of word occurrence reflecting its contributing processes. Inflexitext performance was examined in a sample of 809 English speaking adults in the United States recruited using Amazon's Mechanical Turk platform. Participants wrote essays in response to a prompt to write about an emotional issue and completed self-report measures of distress and psychological flexibility relevant constructs. Participant essays were analyzed using Inflexitext and Linguistic Inquiry Word Count 2015 (LIWC), a popular text scoring program. Inflexitext scores demonstrated small positive correlations to self-report measures of experiential avoidance, cognitive fusion, challenges in progress towards one's values, and to symptoms of depression, anxiety, and stress and a medium positive correlation with LIWC coding of negative emotion. Inflexitext scores evidenced small negative correlations with progress towards one's values and LIWC scores on positive emotion. Overall, this initial examination provides preliminary support for the program, although further evaluation is needed and limitations are discussed. Potential applications for future development include unobtrusive ambient monitoring of verbal behavior and real time examination of psychological inflexibility as related to psychological functioning and therapeutic outcomes.

Our society has become increasingly technologically connected: in the United States 81% of adults own smartphones and 90% are on the internet (Anderson, 2019; Pew Research Center, 2019). Because of our relationship with technology, we interact with sensors and applications that may gather behavioral data. A growing field of digital phenotyping focuses on using this information to improve our understanding of psychological difficulties and support their treatment (Insel, 2017; Torous et al., 2017). Mobile phone sensors can access language used, number of social contacts, physical activity, location, and other information (Harari et al., 2016). They can provide continuous unobtrusive monitoring of behavior and offer insight into its temporal variability (Aung et al., 2017). Data obtained using these methods may be less vulnerable to some sources of error, such as challenges with retrospective recall and social desirability bias (Berkout, Cathey, & Kellum, 2019). Gathering smartphone sensor data is also less burdensome than other methods, which may require participants to carry additional devices or respond to survey questions (Torous et al., 2017). With appropriate considerations for informed consent and privacy, these tools can be used to gather idiographic data, which might offer greater insight into processes contributing to dysfunction and therapeutic change (Hayes et al., 2019).

Recent studies have supported the potential utility of the digital phenotyping approach (Insel, 2017). Ben-Zeev et al. (2015) found that smartphone sensor geospatial activity and sleep duration were negatively related to reported stress. Minor et al. (2018) demonstrated that unobtrusively recorded audio data differentiated individuals high and low in schizotypy symptoms. Individuals who were high in schizotypy evidenced greater negative affect and lower social engagement compared to those low in schizotypy (Minor et al., 2018). Despite the potential utility of these approaches, data available to smartphones is unstructured and necessitates the development of methods to extract meaningful information (Aung et al., 2017).

For verbal humans, language data can be helpful for understanding behavior. Language may alter our response to environmental

* Corresponding author. 6300 Ocean Drive, Corpus Christi, TX, 78412, United States.
E-mail address: oberkout@gmail.com (O.V. Berkout).

https://doi.org/10.1016/j.jcbs.2020.09.002
Received 10 January 2020; Received in revised form 5 August 2020; Accepted 1 September 2020
Available online 7 September 2020
2212-1447/© 2020 Association for Contextual Behavioral Science. Published by Elsevier Inc. All rights reserved.

contingences; a harmless stimulus can become distressing if it is labelled as dangerous (Villatte et al., 2016). Verbal statements have been predictive of subsequent therapeutic outcomes, supporting their utility (Atkins & Styles, 2016; Hesser et al., 2009). Verbal data can offer advantages over questionnaires; it may be less vulnerable to bias and misunderstanding (Berkout, Cathey, & Kellum, 2019). However, such data needs to be categorized to allow for subsequent analysis and use of human coders requires considerable resources. Automated classification can remove the need for resource expenditure and allow for more widespread application.

The psychological flexibility model offers a conceptual framework for organizing verbal data. Psychological flexibility has been defined as the ability to respond adaptively to environmental contingencies, even in the face of challenging thoughts, feelings, and other private events (Levin et al., 2013; Hayes et al., 2013). Psychological inflexibility represents the converse of flexibility and difficulties in values-consistent adaptive responding (Twohig, 2012). Psychological inflexibility is comprised of six contributing processes: experiential avoidance, fusion, challenges with present moment focus, attachment to the conceptualized self, lack of values clarity, and inaction towards one's values (see Levin et al., 2013 for an overview). Greater inflexibility has been linked with stigma, symptoms of depression and anxiety, difficulty coping with chronic pain, aggression, and other difficulties (Berkout, Tinsley, & Flynn, 2019; Krafft et al., 2018; Ruiz, 2010). Inflexibility has also been associated with other challenges, including maladaptive social behavior and lower life satisfaction (Dudek et al., 2015; Gerhart et al., 2014). Acceptance and Commitment Therapy (ACT), which aims to reduce inflexibility, has received empirical support in the treatment of anxiety disorders, mood disorders, psychotic disorders, substance use difficulties, and struggles in coping with chronic pain and other medical conditions (Bluett et al., 2014; McCracken & Vowles, 2014; Twohig, 2012; Wakefield et al., 2018). Given the empirical support obtained for the psychological flexibility model and its transdiagnostic utility, this theoretical framework may offer a useful way to organize unstructured data.

The purpose of the current paper is to describe the development and initial support for Inflexitext, a program for identifying psychological inflexibility in unstructured verbal data. We examined Inflexitext performance on essay data in relation to scores obtained using Linguistic Inquiry Word Count (LIWC) 2015, a widely used text classification software, and self-report measures. We expected that text inflexibility would relate positively to questionnaires measuring experiential avoidance, cognitive fusion, challenges in making progress towards one's values, and to symptoms of depression, anxiety, and stress. Text inflexibility scores were also predicted to negatively relate to self-reported progress towards one's values. Additionally, we expected that text inflexibility scores would correlate positively with LIWC text scores for negative emotion and negatively with its measure of positive emotion.

1. Method

1.1. Inclusion and exclusion criteria

Participant inclusion criteria were being over the age of 18, speaking English, and living within the United States. There were no exclusion criteria beyond meeting these requirements.

1.2. Participants

Participants included in analyses were 809 adults residing in the United States and recruited through Amazon's Mechanical Turk platform. Demographic information is presented for these individuals. Among participants 64.6% identified as female and 35% identified as male. Participants ranged in age from 18 to 81, with a mean of 37.75 and a standard deviation of 12.68. Regarding ethnicity, 9.9% of participants identified as African American/Black, 7.2% as Asian/Asian American, 73.1% as Caucasian/White, 6.2% as Hispanic/Latino, 2% as Multiracial, 0.9% as Native American, and 0.7% as Other. Regarding educational attainment, 0.7% reported having completed high school or less, 7.3% having a high school diploma or General Educational Development (GED) credential, 22.1% some college or technical training, 11.9% associate degree or college certificate, 37.7% a bachelor's degree, 3.8% some graduate school, 14.3% master's degree, and 2.0% doctorate degree. Regarding religious orientation 19.9% identified as Agnostic, 12.9% as Atheist, 1.1% as Buddhist, 55.7% as Christian, 0.7% as Hindu, 2,8% as Jewish, 1.2% as Muslim, and 5.4% as Other.

1.3. Procedures

The study was approved by the Texas A&M Corpus Christi Institutional Review Board. Participants were drawn from Amazon's Mechanical Turk, an online platform that can be used to recruit individuals to complete tasks, including web surveys and other research (Chan & Holosko, 2015). Participants were directed to Qualtrics survey administration software and completed measures in random order. Participants received $0.30 for survey completion.

2. Inflexitext program

2.1. Scoring rule development

Rules for the six psychological inflexibility processes (i.e., experiential avoidance, fusion, challenges in present moment attention, attachment to the conceptualized self, lack of values clarity, and inaction towards one's values; Levin et al., 2013) were developed by drawing on the definitions of constructs used in the literature (Hayes et al., 2012; Luoma et al., 2007). Feedback on these rules was obtained from clinicians and researchers working within the psychological flexibility framework. Detailed descriptions of how these were implemented are available in the Supplemental Materials document. As an example, experiential avoidance was conceptualized as reflected in three processes: nonacceptance of private events, substance use avoidance of private events, and behavioral avoidance related to private events. Behavioral avoidance was defined as the occurrence of a reference to oneself (I, me) in the same sentence as a term for a private event (thought, emotion, memory), with a term indicative of behavioral avoidance (leave, avoid), and without negation (don't, not, can't). We focused on sentences, rather than individual words, to contextualize word use (e.g., the use of "angry" in "I am angry" differs from that in "She is angry"). We chose sentences, rather than larger chunks of data, such as paragraphs, because we hoped to identify statements that were complete, but brief enough to be classified with scholar created rules. We used a researcher generated rule development framework, rather than other approaches to language analysis, such as machine learning, because rule-based techniques can perform adequately within smaller samples and are more easily understood (Hernandez & Hazem, 2018; Murphy, 2017).

2.2. Word list generation

Initial terms were generated conceptually and by drawing on self-report measures. Due to the considerable variability inherent in language, this initial effort focused on processes as they relate to affective difficulties, which included disgust, anxiety, depression, fear, trauma related responding, anger, stress, shame, and general negative affect. To identify terms associated with emotional difficulties, we drew on the PROMIS (Patient-Reported Outcomes Measurement Information System) item banks (Cella et al., 2010; Cook et al., 2016) for Anger, Anxiety/Fear, Depression/Sadness, Emotional and Behavioral Dyscontrol, and Stress. Additionally, to strengthen lists of terms related to the psychological flexibility model processes, we examined measures of psychological inflexibility (the Comprehensive Assessment of Acceptance and Commitment Therapy Processes; Francis et al., 2016; Multidimensional Psychological Flexibility Inventory; Rolffs et al., 2016), experiential avoidance (Acceptance and Action Questionnaire-II; Bond et al., 2011), values and action or inaction towards these (Valued Living Questionnaire; Wilson et al., 2010; Valuing Questionnaire; Smout et al., 2014), cognitive fusion (Cognitive Fusion Questionnaire; Gillanders et al., 2014), and present moment focus (Five Factor Mindfulness Questionnaire; Baer et al., 2006; Mindful Attention Awareness Scale; Brown & Ryan, 2003; Philadelphia Mindfulness Scale, Cardaciotto et al., 2008). Expansion of word lists was further undertaken through searching for synonyms using thesaurus.com and urbandictionary.com (a popular slang website).

2.3. Preprocessing and inflexibility scoring

Scoring was conducted using Python 3.7 (Python Software Foundation, 2018). Python is a widely used open source object-oriented programming language, which has a number of applications, including working with language data. Text was preprocessed through lowering of capital letters (making “Angry” and “angry” equivalent) and tokenization (marking words as chunks of information) prior to analyses. Because we worked only with words that were relevant to our patterns (see Fig. 1 for an example), we did not remove stopwords (typically irrelevant but very common words, such as “an” or “the”) during preprocessing. We did not use stemming or lemmatization, techniques which simplify data by cutting off word endings or collapsing word variations (e.g., equating “cry” and “crying”), because we accounted for

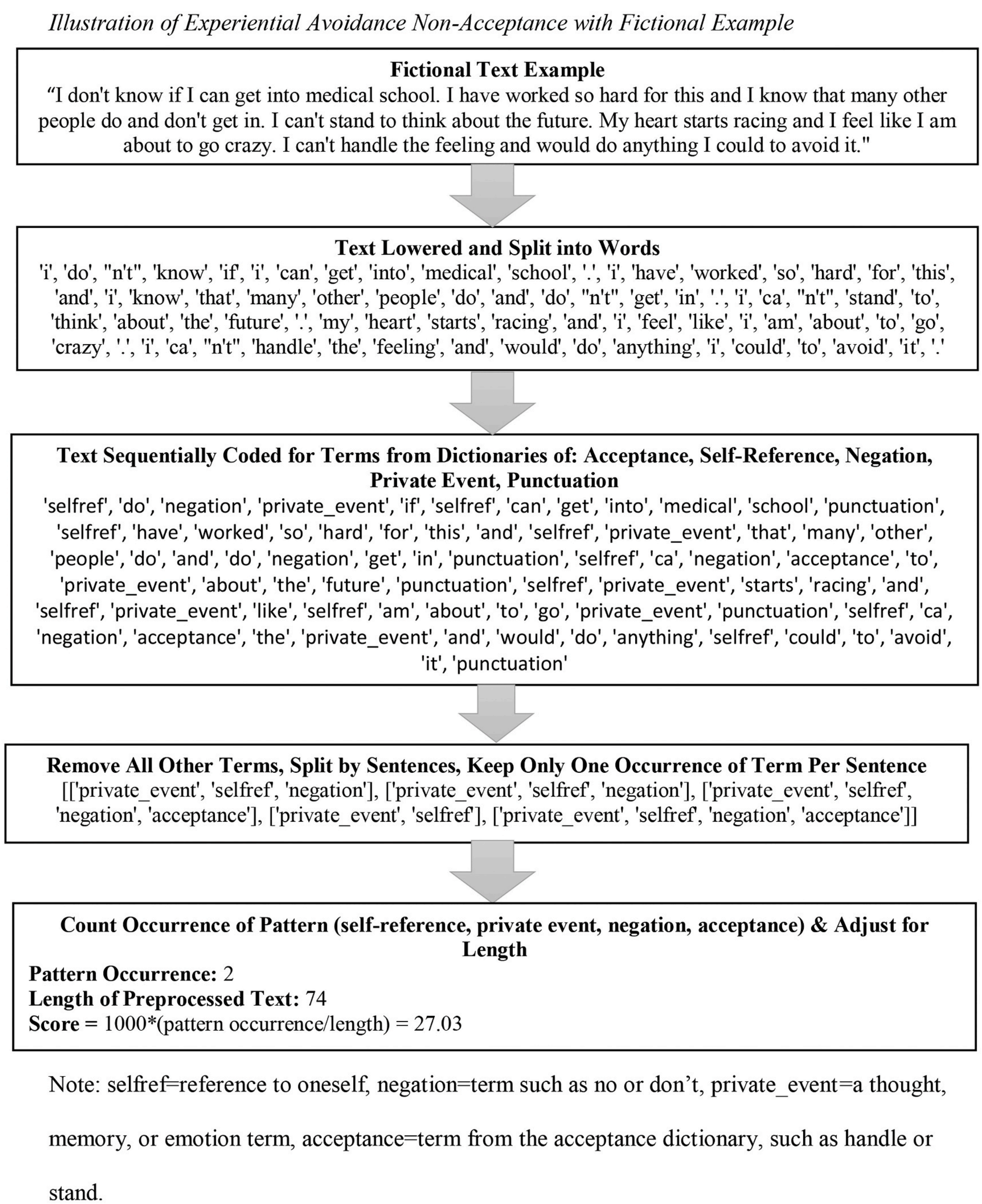

Fig. 1. Illustration of Experiential Avoidance Non-Acceptance with Fictional Example. Note: selfref = reference to oneself, negation = term such as no or don’t, private_event = a thought, memory, or emotion term, acceptance = term from the acceptance dictionary, such as handle or stand.

these aspects of word variability within our dictionaries and wanted to avoid potential error that can occur with application of these techniques. Text was coded so that the occurrence of each pattern was counted and, if applicable, multiple patterns were summed (e.g., nonacceptance, substance use avoidance, and behavioral avoidance represented experiential avoidance). This value was divided by the number of words provided, and multiplied by 1000 to produce numbers that were easier to work with (see Supplemental Material for detailed descriptions). These scores were then summed to provide a text inflexibility score (Python code needed to perform this task is available upon request and may be used freely for academic purposes). Fig. 1 offers an illustrative example of how the non-acceptance pattern within experiential avoidance was scored.

3. Questionnaires

Demographic information on participant gender, age, ethnicity, educational attainment, and religious orientation was collected.

Acceptance and Action Questionnaire-II (AAQ-II; Bond et al., 2011) is a seven-item questionnaire assessing experiential avoidance, or maladaptive efforts to avoid challenging thoughts, feelings, and other experiences (Hayes et al., 2012). Participants indicate the extent to which statements reflective of this process apply to them on a seven-point scale (1 = *never true* to 7 = *always true*). Higher scores on the AAQ-II indicate greater experiential avoidance and psychometric support for this measure has been obtained (Bond et al., 2011). In the present sample, the internal consistency was found to be $\alpha = 0.94$.

Valuing Questionnaire (VQ; Smout et al., 2014) is a 10-item measure assessing the extent to which individuals engaged in behaviors consistent with their values (an aspect of psychological flexibility) or had challenges in doing so (reflective of inflexibility) over the past week. VQ produces two scales, Progress and Obstruction, with higher scores on these reflecting progress towards one's values and challenges in doing so, respectively. Participants provide responses on a seven-point scale (0 = *not at all true* to 6 = *completely true*). Due to an error the *completely true* anchor was presented as *always true*. Internal consistency reliability was $\alpha = 0.85$ for VQ Progress and $\alpha = 0.87$ for VQ Obstruction.

Cognitive Fusion Questionnaire (CFQ; Gillanders et al., 2014) is a seven-item measure developed to assess cognitive fusion, an aspect of psychological inflexibility that is defined by excessive attachment and rigidity related to thoughts. CFQ asks individuals to rate the extent to which they struggle with various aspects of cognitive fusion on a seven-point scale (1 = *never true* to 7 = *always true*) with higher scores reflecting greater fusion. Psychometric support for the CFQ has been obtained (Gillanders et al., 2014). Internal consistency in the present sample was $\alpha = 0.96$.

Depression Anxiety Stress Scales (DASS-21; Lovibond & Lovibond, 1995) is a 21-item measure evaluating the frequency with which respondents report experiencing symptoms of stress, depression, and anxiety. Responses are obtained using a four-point scale (0 = *never* to 3 = *almost always*) and three scales, Depression, Anxiety, and Stress, can be calculated. Internal consistencies in the present study were $\alpha = 0.93$ for DASS Depression, $\alpha = 0.88$ for DASS Anxiety, and $\alpha = 0.88$ for DASS Stress.

3.1. Essay prompt

To produce verbal data participants were asked to respond to an essay prompt. Adapted from Pennebaker (1997), this prompt asks participants to write about an emotional topic that was important to them and to explore their thoughts, feelings, and the impact this topic has had on their lives and relationships with others. This essay prompt and its adaptations has been widely used in expressive writing and linguistic research (Pennebaker, 2017).

3.2. LIWC scores

Essay data was scored using LIWC 2015 (Pennebaker, Booth, et al., 2015). LIWC is a widely used program that analyzes text and provides scores associated with predetermined word categories (Pennebaker, Boyd, et al., 2015). We focused on two LIWC categories relevant to psychological difficulty and well-being: negative emotion, which includes terms, such as ugly, nasty, and hurt, and positive emotion, which includes terms, such as nice, sweet, and love (Pennebaker, Boyd, et al., 2015). These categories were chosen due to relationships between psychological inflexibility and greater distress and poorer well-being demonstrated in the literature (Berkout, Tinsley, & Flynn, 2019; Dudek et al., 2015; Gloster et al., 2017; Ruiz, 2010). Additionally, the positive emotion and negative emotion LIWC categories have evidenced relationships to relevant constructs in other examinations. Individual use of words in the negative emotion category has been associated with depression diagnoses ($\beta = 0.14$; $p = 0.002$; Eichstaedt et al., 2018). Positive emotion terms have been related to greater relationship satisfaction ($r = 0.25$, $p < 0.05$; Robinson et al., 2019) and greater positive affect ($r = 0.19$, $p < 0.01$; Tov et al., 2013). Although we were not able to identify studies of psychological inflexibility and LIWC, we were able to find an examination of these LIWC categories and self-acceptance. As acceptance of challenging thoughts and feelings is an aspect of psychological flexibility, self-acceptance may be viewed as related to this broader construct. Self-acceptance was associated with greater LIWC positive emotion (r's ranging from 0.17 $p < 0.05$ to 0.25, $p < 0.01$) and negatively related to LIWC negative emotion (r's ranging from −0.15 to −0.19, ps < 0.05; Tibubos et al., 2019).

3.3. Data diagnostics

Data from 1915 participants were collected. As the focus of this examination was on analysis of unstructured verbal data, participants who did not complete the essay portion of the study ($n = 805$) were not included. An additional 109 participants responded incorrectly to at least one of three attention check items (e.g., "Please select 1 if you are reading this question") and were classified as random responders and removed. Among the remaining participants, responses were briefly scanned for readily apparent problems. Such problems were identified among 192 responses leaving 809 participants for final analyses. Problems included duplicate submissions ($n = 4$), essays not written in English or deviating from English to such an extent that responses could not be understood ($n = 43$), and not following essay directions ($n = 145$). Examples of not following essay directions included copy and pasting essay directions as the response or providing feedback on the research project rather than writing about an important emotional topic and its impact on the participant lives.

We examined the distribution of Inflexitext inflexibility scores to determine whether they demonstrated sufficient range. These scores ranged from 0 to 159.09 and only 2.6% of the sample obtained 0 scores, suggesting that there was variability in text inflexibility. Skew and kurtosis values suggested that text inflexibility and LIWC negative emotion scores were not normally distributed and histograms confirmed that distributions differed from normal. Given the larger sample size, the shape of the distribution, rather than inference tests were used, as inference tests can identify even minor deviations from normality as significant in larger samples (Tabachnik & Fidel, 2013).

3.4. Analytic strategy

Statistical analyses were conducted using SPSS 25. We obtained descriptive information on the variables included in analyses. We used correlations to examine relationships between Inflexitext inflexibility scores, LIWC positive and negative emotion scores, and self-report measures of experiential avoidance, cognitive fusion, progress towards and challenges in pursuing one's values, and symptoms of depression, anxiety, and stress.

4. Results

Descriptive information on text inflexibility and other measures is presented in Table 1. After data cleaning procedures, 0.6% of cases contained any missing values, suggesting that missing data was unlikely to influence analyses.

4.1. Relationships between text inflexibility and self report measures

Relationships between Inflexitext inflexibility and self-report measures were examined, along with those for LIWC categories for comparison, presented in Table 2. Given the deviation from normality of text measures, Spearman's rho, rather than Pearson's r was used to avoid potential inflation of Type I error (Bishara & Hittner, 2012). Text inflexibility was positively related to questionnaires measuring experiential avoidance, cognitive fusion, and challenges in pursuing one's values and to symptoms of depression, anxiety, and stress. Text inflexibility was negatively related to progress towards one's values.

4.2. Relationship between text inflexibility and LIWC categories

Spearman's rho correlations between Inflexitext inflexibility and LIWC positive and negative emotion were also computed, presented in Table 3. Inflexibility was associated with negative emotion and negatively related to positive emotion scores.

5. Discussion

The current study describes the development of Inflexitext, a program for identifying psychological inflexibility in unstructured verbal data. One of the challenges with developing approaches for scoring verbal data is the variability present within language. As such, ensuring that Inflexitext was able to successfully identify some occurrence of inflexibility was important. Our examination suggested that text inflexibility scores had sufficient variability: scores ranged from 0 to 159.09 and few essays had no instances of inflexibility (2.6%). This finding suggests that, even in a small subset of data, Inflexitext is able to identify psychological inflexibility. The psychological inflexibility text scores were not normally distributed, consistent with the tendency of text data to perform differently than questionnaires (Tausczik & Pennebaker, 2009). Scholars interested in using these metrics will need to attend to data distribution and consider implications for statistical analyses.

Relationships between text psychological inflexibility and conceptually related measures were examined. We found that text inflexibility was positively related to questionnaires assessing psychological inflexibility processes (experiential avoidance, cognitive fusion, challenges in pursuing one's values) and negatively related to those consistent with psychological flexibility (progress towards one's values). Text psychological inflexibility was also positively related to questionnaire scales measuring depression, anxiety, and stress, consistent with the broader literature linking psychological inflexibility and psychological difficulties (Berkout, Tinsley, & Flynn, 2019; Krafft et al., 2018; Ruiz, 2010). Relationships obtained were small, but comparable in size to those between self-report measures and LIWC positive and negative emotion text scores. These were also similar in magnitude to those obtained using LIWC software and self-report measures within the literature (Tackman et al., 2019).

We obtained the predicted relationships between text inflexibility and LIWC categories of positive and negative emotion. Psychological inflexibility was associated with greater negative emotion and lower positive emotion expressed in text. These findings were consistent with the broader literature on psychological inflexibility and its associations with psychopathology and well-being. The relationship between inflexibility and negative emotion was stronger than that demonstrated for positive emotion and this finding may merit further examination. In sum, this initial study provided support for Inflexitext ability to identify psychological inflexibility in unstructured verbal data.

Additionally, the program was written in Python 3.7, an open source programming language, which is both freely available and user friendly to beginner programmers. Python is among the most widely used programming languages and has a large active community of users, supporting the development of libraries and online forums where specific applications are discussed. Python has numerous libraries that may be used for monitoring behavior and statistical analysis. These include libraries for audio recording (PyAudio; Pham, 2006), speech recognition (SpeechRecognition, Zhang, 2017), mobile app development (Kivy; Kivy Team, 2019), statistics (StatsModels; Seabold & Perktold, 2010), and machine learning (Scikit-Learn; Pedregosa et al., 2011). Inflexitext could be easily integrated with these libraries to support the collection and analysis of verbal data.

5.1. Limitations

Although the current study contributes to the literature base and represents, to our knowledge, the first effort to develop a rule-based system examining psychological inflexibility in unstructured verbal data, our approach is not without limitations. Our study used cross-sectional data, which does not allow for conclusions about predictive utility. Text inflexibility scores were compared to a limited subset of self-report measures and LIWC text scores. Additionally, although LIWC is a widely used text scoring program (Pennebaker, Boyd, et al., 2015) some scholars have raised concerns about its category scores. For example, Sun et al. (2020) failed to find relationships between LIWC emotion scores in daily language and participant self-reports of their emotional states (Sun et al., 2020). Additionally, scholars using LIWC cannot access the dictionaries that are used to generate these scores. As LIWC is a paid program with resources devoted to its development, its creators may not wish to share these dictionaries as they could be used to easily reproduce its functionality (Berkout, Cathey, & Kellum, 2019). At the same time a lack of transparency in the manner in which constructs are measured may make it more challenging for scholars to make informed decisions in interpreting results (Flake & Fried, 2019).

Although the essay task administered in the current study has been widely used in psychological research, it differs from contexts in which verbal data may be generated in daily life. Sun et al. (2020) point out that analytic methods that are effective in scoring essay text may not perform as well for spoken language or social media posts. Research examining the applicability of this scoring system within naturally generated data is needed to ensure its viability.

Finally, there are some inherent downsides to using a rule-based text scoring system. Although such an approach is better able to contextualize language than analysis examining word occurrence alone, it has

Table 1
Descriptive statistics of measures.

Measure	Mean (Standard Deviation)	Skew	Kurtosis
AAQ-II	23.00 (11.36)	0.28	−0.92
CFQ	25.78 (11.52)	0.09	−0.93
VQ-Progress	18.08 (6.26)	−0.34	−0.11
VQ-Obstruction	12.41 (7.26)	0.07	−0.80
DASS Depression	11.88 (10.40)	0.84	−0.04
DASS Anxiety	9.45 (9.02)	0.94	0.15
DASS Stress	13.77 (8.79)	0.45	−0.14
LIWC Positive Emotion	2.98 (1.82)	0.96	1.37
LIWC Negative Emotion	3.43 (2.27)	1.80	7.87
Inflexitext Text Inflexibility	34.66 (20.52)	1.50	4.71

Note: AAQ-II = Acceptance and Action Questionnaire-II; CFQ=Cognitive Fusion Questionnaire; VQ = Valuing Questionnaire; DASS = Depression Anxiety Stress Scales-21; LIWC = Linguistic Inquiry Word Count 2015.

Table 2
Spearman's rho correlations between text scores and self report measures.

	AAQ-II	CFQ	VQ-P	VQ-O	DASS-D	DASS-A	DASS-S
Inflexitext Psychological Inflexibility	0.15** (0.08–0.22)	0.14** (0.07–0.21)	−0.18** (−0.25 to −0.12)	0.11** (0.04–0.18)	0.17** (0.10–0.23)	0.12** (0.05–0.18)	0.12** (0.06–0.19)
LIWC Negative Emotion	0.18** (0.11–0.24)	0.14** (0.07–0.20)	−0.11** (−0.17 to −0.04)	0.12** (0.05–0.18)	0.14** (0.07–0.20)	0.12** (0.05–0.18)	0.13** (0.06–0.20)
LIWC Positive Emotion	−0.06 (−0.12 to 0.01)	−0.05 (−0.11 to 0.02)	0.10** (0.04–0.17)	−0.05 (−0.12 to 0.02)	−0.10** (−0.16 to −0.03)	−0.05 (−0.12-0.01)	−0.04 (−0.11 to 0.03)

Note: AAQ-II = Acceptance and Action Questionnaire-II; CFQ=Cognitive Fusion Questionnaire; VQ-P= Valuing Questionnaire Progress; VQ-O= Valuing Questionnaire Obstruction; DASS-D = Depression Anxiety Stress Scales-21 Depression; DASS-A = Depression Anxiety Stress Scales-21 Anxiety; DASS-S = Depression Anxiety Stress Scales-21 Stress; LIWC = Linguistic Inquiry Word Count 2015. 95% confidence intervals are indicated in parentheses, calculated using VassarStats (Lowry, 2019). $p < 0.01$ is indicated with **; $p \leq 0.05$ is indicated by *.

Table 3
Spearman's Rho Correlations Between Inflexitext and LIWC Scores.

	LIWC Negative Emotion	LIWC Positive Emotion
Inflexitext Psychological Inflexibility	0.30** (0.24–0.36)	−0.09** (−0.16 to −0.02)
LIWC Positive Emotion	−0.20** (−0.26 to −0.13)	

Note: LIWC = Linguistic Inquiry Word Count 2015. 95% confidence intervals are indicated in parentheses, calculated using VassarStats (Lowry, 2019). $p < 0.01$ is indicated with **; $p \leq 0.05$ is indicated by *.

some disadvantages. Rule-based systems rely on scholars to generate a structure, which is sufficiently successful at capturing constructs of interest in highly variable language data. Compared to machine learning algorithms, rule-based systems are harder to modify in response to changing norms; however, they also tend to be easier to understand and do not require very large datasets for sufficient performance (Hernandez & Hazem, 2018).

6. Conclusions and future directions

The current study represents an initial effort to develop a rule-based system for classifying verbal data using open source Python 3.7 software. Identification of patterns consistent with psychological inflexibility and other psychological constructs in unstructured data available through our interactions with technology may extend our understanding of human behavior and processes contributing to dysfunction and therapeutic change. Subsequent examinations with more extensive validation efforts, integration of other behavioral measures, and studies examining predictive validity, are needed to continue to advance this strategy.

Author note

Python code used in the study is freely available for academic use and may be obtained by contacting the corresponding author. Study supported by funding from Texas A&M University Corpus Christi. We have no conflicts of interest to disclose.

Declaration of competing interest

This project was internally funded by the corresponding author's institution. We have no conflicts of interest to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2020.09.002.

References

Anderson, M. (2019). *June 13). Mobile technology and home broadband 2019*. Pew Research Center. https://www.pewresearch.org/internet/2019/06/13/mobile-technology-and-home-broadband-2019/.

Atkins, P. W. B., & Styles, R. G. (2016). Measuring self and rules in what people say: Exploring whether self-discrimination predicts long-term wellbeing. *Journal of Contextual Behavioral Science, 5*(2), 71–79. https://doi.org/10.1016/j.jcbs.2016.05.001.

Aung, M. H., Matthews, M., & Choudhury, T. (2017). Sensing behavioral symptoms of mental health and delivering personalized interventions using mobile technologies. *Depression and Anxiety, 34*(7), 603–609. https://doi.org/10.1002/da.22646.

Baer, R. A., Smith, G. T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. *Assessment, 13*(1), 27–45. https://doi.org/10.1177/1073191105283504.

Ben-Zeev, D., Scherer, E. A., Wang, R., Xie, H., & Campbell, A. T. (2015). Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. *Psychiatric Rehabilitation Journal, 38*(3), 218–226. https://doi.org/10.1037/prj0000130.

Berkout, O. V., Cathey, A. J., & Kellum, K. K. (2019a). Scaling-up assessment from a contextual behavioral science perspective: Potential uses of technology for analysis of unstructured text data. *Journal of Contextual Behavioral Science, 12*, 216–224. https://doi.org/10.1016/j.jcbs.2018.06.007.

Berkout, O. V., Tinsley, D., & Flynn, M. K. (2019b). A review of anger, hostility, and aggression from an ACT perspective. *Journal of Contextual Behavioral Science, 11*, 34–43. https://doi.org/10.1016/j.jcbs.2018.12.001.

Bishara, A. J., & Hittner, J. B. (2012). Testing the significance of a correlation with nonnormal data: Comparison of Pearson, Spearman, transformation, and resampling approaches. *Psychological Methods, 17*(3), 399–417. https://doi.org/10.1037/a0028087.

Bluett, E. J., Homan, K. J., Morrison, K. L., Levin, M. E., & Twohig, M. P. (2014). Acceptance and commitment therapy for anxiety and OCD spectrum disorders: An empirical review. *Journal of Anxiety Disorders, 28*(6), 612–624. https://doi.org/10.1016/j.janxdis.2014.06.008.

Bond, F. W., Hayes, S. C., Baer, R. A., Carpenter, K. M., Guenole, N., Orcutt, H. K., Waltz, T., & Zettle, R. D. (2011). Preliminary psychometric properties of the acceptance and action questionnaire–II: A revised measure of psychological inflexibility and experiential avoidance. *Behavior Therapy, 42*(4), 676–688, 10.1016%2Fj.beth.2011.03.007.

Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: Mindfulness and its role in psychological well-being. *Journal of Personality and Social Psychology, 84*(4), 822–848. https://doi.org/10.1037/0022-3514.84.4.822.

Cardaciotto, L., Herbert, J. D., Forman, E. M., Moitra, E., & Farrow, V. (2008). The assessment of present-moment awareness and acceptance. *Assessment, 15*(2), 204–223. https://doi.org/10.1177/1073191107311467.

Cella, D., Riley, W., Stone, A., Rothrock, N., Reeve, B., Yount, S., Amtmann, D., Bode, R., Buysse, D., Choi, S., Cook, K., DeVellis, R., DeWalt, D., Fries, J. F., Gershon, R., Hahn, E. A., Lai, J. S., Pilkonis, P., Revicki, Hays, D., & R. (2010). Initial adult health item banks and first wave testing of the patient-reported outcomes measurement information system (PROMIS) network: 2005-2008. *Journal of Clinical Epidemiology, 63*(11), 1179–1194. https://doi.org/10.1016/j.jclinepi.2010.04.011.

Chan, C., & Holosko, M. J. (2015). An overview of the use of Mechanical Turk in behavioral sciences. *Research on Social Work Practice, 26*(4), 441–448. https://doi.org/10.1177/1049731515594024.

Cook, K. F., Jensen, S. E., Schalet, B. D., Beaumont, J. L., Amtmann, D., Czajkowski, S., Dewalt, D. A., Fries, J. F., Pilkonis, P. A., Reeve, B. B., Stone, A. A., Weinfurt, K. P., & Cella, D. (2016). PROMIS measures of pain, fatigue, negative affect, physical function, and social function demonstrated clinical validity across a range of chronic conditions. *Journal of Clinical Epidemiology, 73*, 89–102. https://doi.org/10.1016/j.jclinepi.2015.08.038.

Dudek, J. E., Białaszek, W., & Ostaszewski, P. (2015). Quality of life in women with lipoedema: A contextual behavioral approach. *Quality of Life Research, 25*(2), 401–408. https://doi.org/10.1007/s11136-015-1080-x.

Eichstaedt, J. C., Smith, R. J., Merchant, R. M., Ungar, L. H., Crutchley, P., Preoţiuc-Pietro, D., Asch, D. A., & Schwartz, H. A. (2018). Facebook language predicts depression in medical records. *Proceedings of the National Academy of Sciences, 115*(44), 11203–11208. https://doi.org/10.1073/pnas.1802331115.

Flake, J. K., & Fried, E. I. (2019). *Measurement schmeasurement: Questionable measurement practices and how to avoid them*, 10.31234/osf.io/hs7wm.
Francis, A. W., Dawson, D. L., & Golijani-Moghaddam, N. (2016). The development and validation of the comprehensive assessment of acceptance and commitment therapy processes (CompACT). *Journal of Contextual Behavioral Science, 5*(3), 134–145. https://doi.org/10.1016/j.jcbs.2016.05. 003.
Gerhart, J. I., Baker, C. N., Hoerger, M., & Ronan, G. F. (2014). Experiential avoidance and interpersonal problems: A moderated mediation model. *Journal of Contextual Behavioral Science, 3*(4), 291–298. https://doi.org/10.1016/j.jcbs.2014.08.003.
Gillanders, D., Bolderston, H., Bond, F. W., Dempster, M., Flaxman, P. E., Campbell, L., Kerr, S., Tansey, L., Noel, P., Ferenbach, C., Masley, S., Roach, L., Lloyd, J., May, L., Clarke, S., & Remington, B. (2014). The development and initial validation of the Cognitive Fusion Questionnaire. *Behavior Therapy, 45*(1), 83–101. https://doi.org/10.1016/j.beth.2013.09.001.
Gloster, A. T., Meyer, A. H., & Lieb, R. (2017). Psychological flexibility as a malleable public health target: Evidence from a representative sample. *Journal of Contextual Behavioral Science, 6*(2), 166–171. https://doi.org/10.1016/j.jcbs.2017.02.003.
Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T., & Gosling, S. D. (2016). Using smartphones to collect behavioral data in psychological science. *Perspectives on Psychological Science, 11*(6), 838–854. https://doi.org/10.1177/1745691616650285.
Hayes, S. C., Hofmann, S. G., Stanton, C. E., Carpenter, J. K., Sanford, B. T., Curtiss, J. E., & Ciarrochi, J. (2019). The role of the individual in the coming era of process-based therapy. *Behaviour Research and Therapy, 117*, 40–53. https://doi.org/10.1016/j.brat.2018.10.005.
Hayes, S. C., Levin, M. E., Plumb-Vilardaga, J., Villatte, J. L., & Pistorello, J. (2013). Acceptance and commitment therapy and contextual behavioral science: Examining the progress of a distinctive model of behavioral and cognitive therapy. *Behavior Therapy, 44*(2), 180–198. https://doi.org/10.1016/j.beth.2009.08.002.
Hayes, S. C., Strosahl, K. D., & Wilson, K. G. (2012). *Acceptance and Commitment Therapy: The process and practice of mindful change*. Guilford Press.
Hernandez, N., & Hazem, A. (2018). PyRATA Python rule-based feature structure analysis. In N. Calzolari, K. Choukri, C. Cieri, T. Declerck, K. Hasida, H. Isahara, B. Maegaard, J. Mariani, A. Moreno, J. Odijk, S. Piperidis, & T. Tokunaga (Eds.), *Proceedings of the eleventh international Conference on language Resources and evaluation (LREC 2018)* (pp. 2093–2098). European Language Resources Association https://www.aclweb.org/anthology/volumes/L18-1/.
Hesser, H., Westin, V., Hayes, S. C., & Andersson, G. (2009). Clients' in-session acceptance and cognitive defusion behaviors in acceptance-based treatment of tinnitus distress. *Behaviour Research and Therapy, 47*(6), 523–528. https://doi.org/10.1016/j.brat.2009.02.002.
Insel, T. R. (2017). Digital phenotyping: Technology for a new science of behavior. *Journal of the American Medical Association, 318*(13), 1215–1216. https://doi.org/10.1001/jama.2017.11295.
Kivy Team. (2019). *Kivy*. MIT. https://kivy.org/#home.
Krafft, J., Ferrell, J., Levin, M. E., & Twohig, M. P. (2018). Psychological inflexibility and stigma: A meta-analytic review. *Journal of Contextual Behavioral Science, 7*, 15–28. https://doi.org/10.1016/j.jcbs.2017.11.002.
Levin, M. E., Hayes, S. C., & Vilardaga, R. (2013). Acceptance and Commitment Therapy: Applying an iterative translational research strategy in behavior analysis. In G. J. Madden, W. V. Dube, T. D. Hackenberg, G. P. Hanley, & K. A. Lattal (Eds.), *Translating principles into practice: Vol. 2. APA handbook of behavior analysis* (pp. 455–479). https://doi.org/10.1037/13938-018.
Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the depression anxiety stress scales (DASS) with the beck depression and anxiety inventories. *Behaviour Research and Therapy, 33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-u.
Lowry, R. (2019). *VassarStats*. http://vassarstats.net/rho.html.
Luoma, J. B., Hayes, S. C., & Walser, R. D. (2007). *Learning ACT: An Acceptance & Commitment Therapy skills training manual for therapists*. New Harbinger Publications.
McCracken, L. M., & Vowles, K. E. (2014). Acceptance and Commitment Therapy and mindfulness for chronic pain: Model, process, and progress. *American Psychologist, 69* (2), 178–187. https://doi.org/10.1037/a0035623.
Minor, K. S., Davis, B. J., Marggraf, M. P., Luther, L., & Robbins, M. L. (2018). Words matter: Implementing the electronically activated recorder in schizotypy. *Personality Disorders: Theory, Research, and Treatment, 9*(2), 133–143. https://doi.org/10.1037/per0000266.
Murphy, S. C. (2017). A hands-on guide to conducting psychological research on Twitter. *Social Psychological and Personality Science, 8*(4), 396–412. https://doi.org/10.1177/1948550617697178.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*(85), 2825–2830.
Pennebaker, J. W. (1997). Writing about emotional experiences as a therapeutic process. *Psychological Science, 8*(3), 162–166. https://doi.org/10.1111/j.1467-9280.1997.tb00403.x.
Pennebaker, J. W. (2017). Expressive writing in psychological science. *Perspectives on Psychological Science, 13*(2), 226–229. https://doi.org/10.1177/1745691617707315.
Pennebaker, J. W., Booth, R. J., Boyd, R. L., & Francis, M. E. (2015a). *Linguistic inquiry and word count: LIWC2015*. Pennebaker Conglomerates. www.LIWC.net.
Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015b). *The development and psychometric properties of LIWC2015*. University of Texas at Austin. https://repositories.lib.utexas.edu/bitstream/handle/2152/31333/LIWC2015_LanguageManual.pdf.
Pew Research Center. (2019, June 12). *Internet/broadband fact sheet*. https://www.pewinternet.org/fact-sheet/internet-broadband/.
Pham, H. (2006). *PyAudio. Hubert Pham*. https://pypi.org/project/PyAudio/.
Python Software Foundation. (2018). Python software foundation. *Python* Version 3.7. http://www.python.org.
Robinson, M. D., Persich, M. R., Sjoblom-Schmidt, S., & Penzel, I. B. (2019). Love stories: How language use patterns vary by relationship quality. *Discourse Processes, 57*(1), 81–98. https://doi.org/10.1080/0163853x.2019.1627158.
Rolffs, J. L., Rogge, R. D., & Wilson, K. G. (2016). Disentangling components of flexibility via the hexaflex model: Development and validation of the multidimensional psychological flexibility inventory (MPFI). *Assessment, 25*(4), 458–482. https://doi.org/10.1177/1073191116645905.
Ruiz, F. J. (2010). A review of Acceptance and Commitment Therapy (ACT) empirical evidence: Correlational, experimental psychopathology, component and outcome studies. *International Journal of Psychology and Psychological Therapy, 10*(1), 125–162.
Seabold, S., & Perktold, J. (2010). *StatsModels. Skipper Seabold and josef Perktold*. https://www.statsmodels.org/stable/index.html#citation.
Smout, M., Davies, M., Burns, N., & Christie, A. (2014). Development of the valuing questionnaire (VQ). *Journal of Contextual Behavioral Science, 3*(3), 164–172. https://doi.org/10.1016/j.jcbs.2014.06.001.
Sun, J., Schwartz, H. A., Son, Y., Kern, M. L., & Vazire, S. (2020). The language of well-being: Tracking fluctuations in emotion experience through everyday speech. *Journal of Personality and Social Psychology, 118*(2), 364–387. https://doi.org/10.1037/pspp0000244.
Tabachnik, B. G., & Fidel, L. S. (2013). *Using multivariate statistics* (7th ed.). Pearson.
Tackman, A. M., Sbarra, D. A., Carey, A. L., Donnellan, M. B., Horn, A. B., Holtzman, N. S., Edwards, T. S., Pennebaker, J. W., & Mehl, M. R. (2019). Depression, negative emotionality, and self-referential language: A multi-lab, multi-measure, and multi-language-task research synthesis. *Journal of Personality and Social Psychology, 116*(5), 817–834. https://doi.org/10.1037/pspp0000187.
Tausczik, Y. R., & Pennebaker, J. W. (2009). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24–54. https://doi.org/10.1177/0261927x09351676.
Tibubos, A. N., Köber, C., Habermas, T., & Rohrmann, S. (2019). Does self-acceptance captured by life narratives and self-report predict mental health? A longitudinal multi-method approach. *Journal of Research in Personality, 79*, 13–23. https://doi.org/10.1016/j.jrp.2019.01.003.
Torous, J., Onnela, J.-P., & Keshavan, M. (2017). New dimensions and new tools to realize the potential of RDoC: Digital phenotyping via smartphones and connected devices. *Translational Psychiatry, 7*(3). https://doi.org/10.1038/tp.2017.25. e1053–e1053.
Tov, W., Ng, K. L., Lin, H., & Qiu, L. (2013). Detecting well-being via computerized content analysis of brief diary entries. *Psychological Assessment, 25*(4), 1069–1078. https://doi.org/10.1037/a0033007.
Twohig, M. P. (2012). Acceptance and commitment therapy. *Cognitive and Behavioral Practice, 19*(4), 499–507. https://doi.org/10.1016/j.cbpra.2012.04.003.
Villatte, M., Villatte, J., & Hayes, S. (2016). *Mastering the clinical conversation: Language as intervention*. Guilford Press.
Wakefield, S., Roebuck, S., & Boyden, P. (2018). The evidence base of acceptance and commitment therapy (ACT) in psychosis: A systematic review. *Journal of Contextual Behavioral Science, 10*, 1–13. https://doi.org/10.1016/j.jcbs.2018.07.001.
Wilson, K. G., Sandoz, E. K., Kitchens, J., & Roberts, M. (2010). The Valued Living Questionnaire: Defining and measuring valued action within a behavioral framework. *Psychological Record, 60*(2), 249–272. https://doi.org/10.1007/bf03395706.
Zhang, A. (2017). *SpeechRecognition. Anthony Zhang*. https://pypi.org/project/SpeechRecognition/.