YOUTUBE DISCLOSURE

Linguistic Markers of Self-Disclosure:

Using YouTube Coming Out Videos to Study Disclosure Language

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Traditional attempts at measuring self-disclosure actually measure self-reported perceptions of disclosure – which is conflated with individual difference characteristics – or rely on trained coders – which is time-consuming. Across a pilot and two studies using a known-groups paradigm repeated measure analyzing transcripts from YouTube videos, we measured self-disclosure with an easily-accessible text-analysis software. Focusing on videos in which the speaker “comes out” as having a concealable stigmatized identity (being LGBT, having HIV, having a mental illness), we found support for the utility of this metric for operationalization of disclosure. This output was correlated with trained coders’ ratings and was effective for predicting audience behavior outcomes, including reciprocal disclosure. Finally, we discuss the utility of text-analysis software for theoretical and applied work.

Key words: self-disclosure, YouTube, LIWC

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Self-disclosure, the process by which an individual intentionally shares increasingly intimate information about themselves to others in order to establish interpersonal closeness, is a cornerstone of social psychological and communicative research. Early work explored the existential importance of disclosure for maintaining relationships and fostering a deeper understanding of the self (Jourard, 1966), how extreme levels of disclosure (both too little and too much) is socially undesirable (Cozby, 1972), and measurement models focused on topic-based approaches (Jourard & Lasakow, 1958; Vondracek & Vondracek, 1971). Social penetration theory (Altman & Taylor, 1973), one of the most-cited relational theories in the field of communication, has organized many of these findings into a succinct model, robust across time, culture, and medium (Collins & Miller, 1994).

Despite its well-established position within the social sciences, a majority of attempts to measure disclosure fall into two flawed categories: those that focus on the perceptions of disclosure and those that focus on the outcomes of disclosure. For example, the widely-used scale by Laurenceau and colleagues (1998) asks participants to indicate, using two items, how much they felt they self-disclosed during an interaction. Similarly, the researchers ask participants to judge how much their partner disclosed with three items. These strategies both reflect participants' perceptions of self-disclosure – an important construct but conflated with individual differences including self-consciousness (Shaffer & Tomarelli, 1989) and attachment style (Chen et al., 2019). Without accounting for these covariates, self-reports of disclosure are challenging to interpret.

Other researchers, instead, focus on relevant outcomes when attempting to measure disclosure. Using the Outness Inventory (Mohr & Fassinger, 2000) which is a double-barreled scale that measures how much members of different social groups know about the participants' homosexual identity and how much the participant discusses their identity with these people, Villicana and colleagues claim to measure verbal disclosure (2016, p. 5). At most these researchers are capturing frequency with which participants discuss their identity, but this is different from measuring disclosure itself. While both perceptions and frequency are important components of disclosure, the intimacy of the disclosure itself is overlooked when it comes to attempts at measurement.

The work that does target the intimacy of disclosure traditionally relies on qualitative content analysis by trained coders reading transcripts of interactions (Joinson, 2001; Sermat & Smyth, 1973). This process is time consuming, resource intensive, and increasingly complex as samples become larger (Burnard et al., 2008; Erlingsson & Brysiewicz, 2017). Additionally, disclosure is understood to be situationally dependent (Antaki et al., 2005) which leads to many coding schemes being designed for specific contexts like disclosing infidelity between relationship partners (Walters & Burger, 2013) or therapists disclosing to their clients (Knox et al., 1997).

An instance of self-disclosure, like all messages, is made up of both content words and function words. Take, for example, the following sentences that communicate similar information: "Spiders are terrifying," and, "I am terrified of spiders." While both sentences include the same content - the evaluation of spiders as terrifying - the second communicates an aspect of self while the first states a fact. The difference between these sentences is not the

content, but the function words. Pronouns, prepositions, articles, and conjunctions are indicators of communicative style and, as Alport (1961) suggested, markers of individual differences. Chung and Pennebaker's (2007) review of function words highlight their utility for predicting psychosocial variables reflective of the message itself, the person sending it, and the relational context of the speakers.

Past attempts at developing text-based markers of disclosure have relied, primarily, on number of words in a text (Pedersen & Breglio, 1968), as well as use of first-person pronouns (Barak & Gluck-Ofri, 2007), and emotionality (Levi-Belz & Kreiner, 2016). While these metrics are associated with trained coders' perceptions of disclosure within messages, much of the relationship is explained by the use of first-person pronouns (see Levi-Belz & Kreiner, 2016, p. 236). While the use of first-person pronouns is certainly relevant for disclosure, the metric on its own has been known to be associated with dozens of other concepts including age, gender, and mental health (see Tausczik & Pennebaker, 2010). However, the most recent release of LIWC suggests a new solution.

LIWC2015 (Pennebaker et al., 2015) includes many of the same metrics as its former releases – most of which reflect the percentage of words in an analyzed text that are found in LIWC's carefully-constructed dictionaries relating to topics like positive emotion, work, and swear words. New to the program are summary variables – *Analytic*, *Clout*, *Authentic*, and *Tone*. These variables are still reported as percentiles, but unlike other output, these metrics are standardized composite scores calculated based on other published research. The exact formulas are not publicly available.

One of these summary variables, *Authentic*, is based on research surrounding truthfulness. Researchers found that, in both spoken and written language in five independent samples, a combination of pronouns, negative emotion words (e.g., jealousy, tragic), exclusive words (e.g., but, without), and motion verbs (e.g., move, went) was able to distinguish truth from lies better than both human coders and random chance (Newman et al., 2003). This work, which informed the development of the *Authentic* variable in LIWC2015, is conceptually similar to disclosure – after all, disclosure requires the speaker to be truthful to share intimate aspects of themselves (Fisher, 1984, p. 279). In fact, the LIWC2015 Operator Manual even describes this *Authentic* variable by saying, “higher numbers are associated with a more honest, personal, and disclosing text...” (Pennebaker et al., 2015, p. 22).

The goal of this paper is to validate the claims that LIWC’s *Authentic* variable can adequately identify disclosure in text. To do so, we turn to a unique publicly available dataset: YouTube videos. A large percentage of the billions of hours of video content hosted on YouTube is uploaded by “vloggers” – individuals who post video logs of their lives. These content creators’ networks have become micro-segmented to reflect interests of their audience members; some discuss fashion brands or fitness strategies while others share stories about their day-to-day activities.

In the mid-2010s, a new genre of video emerged after being posted by some popular vloggers. These content creators expressed to their digital audiences that they were lesbian, gay, bisexual, and/or transgender (LGBT). Soon after, other creators shared their similar stories in which they disclose having other concealable stigmatized identities (CSI; Chaudoir & Quinn, 2015; Quinn & Chaudoir, 2009). “Coming Out” videos were quickly shared by fans and garnered

tens of millions of views within a very short period of time. After sharing these videos, many vloggers returned to their typical posts, discussing travel tips, makeup tutorials, and answering fan mail. True to YouTube's motto of "Broadcast Yourself", these YouTubers unintentionally created a robust dataset with which this linguistic marker of disclosure can be validated.

Study 1a

We began by evaluating the linguistic marker of disclosure within an early form of high-disclosure videos: coming out as LGBT. Using a known-groups repeated-measures paradigm, we hypothesized that self-disclosure, measured with both trained coders and LIWC2015's *Authentic* variable, would be higher in coming out videos than in other videos posted by the same creators. We also hypothesized that both measures would positively correlate with each other.

Method

Analyses for all studies were completed in R (R Core Team, 2013) using the *psych* (Revelle, 2018), *lme4* (Bates et al., 2015), and *simr* (Peter Green & Macleod, 2016) packages. All analytic code and data are available as supplementary materials. All multi-level models include creator as a random effect. Studies 1b and 2 also include topic of disclosure as a random effect. Data and analytic code can be found [here](#).

Data Collection

We searched YouTube for videos in which a content creator came out as LGBT to their fans using the search term "coming out LGBT". Videos must have met the following inclusion criteria: the content creator must be the only person in the video, they must directly address their audience (a "vlog" setup), and they must be expressing their CSI – not recounting another

time that they came out to someone else. Once these high disclosure event (HDE) videos were identified, we collected YouTube's automatically generated transcripts, as well as video meta-data including number of comments, views, and date posted. We then identified up to five videos before and five videos after the HDE that followed similar inclusion criteria and collected the same information. A total of 71 transcripts were successfully collected.

Measures

Disclosure Language. LIWC2015 is a text-analysis software that calculates the number of words in a text that fall into various dictionaries. The psychometric properties of LIWC have been well-established elsewhere (Tausczik & Pennebaker, 2010). Newman and colleagues' (2003) work exploring features of truthfulness lead to the generation of a LIWC summary variable called *Authentic*; scores for this variable are standardized and range from 0 to 100 with higher scores indicating more, "honest, personal, and disclosing text" (Pennebaker et al., 2015, p. 22).

Disclosure Ratings. Following protocol. From Barak and Gluck-Ofri (2007) for coding observations of disclosure in online forums, we had trained coders evaluate each transcript for amount of self-disclosure regarding information, thoughts, and feelings using a three-point scale ("low", "medium", and "high"). Coders' ratings were then averaged such that each transcript was assigned a continuous value between 1 and 3 inclusive.

Four coders rated all 71 LGBT coming out videos; interclass correlation. With fixed raters' means (ICC3k; Shrout & Fleiss, 1979) indicate satisfactory inter-rater reliability, $r(70, 210) = .91$, $p < .001$, 95% CI: [.88, .94].

Video. Videos were coded such that HDE was listed as the 0th event, videos posted before the HDE were listed as a negative value, and videos posted after were listed as a positive value. In one case, a creator's coming out video was posted across two separate videos (part one and part two); in this case, both videos were coded as HDE. For planned contrasts, all non-HDE videos were compared to HDE.

Results

A linear mixed model in which videos were nested within creator identified significant differences in disclosure language (LIWC's *Authentic*), $F(10, 54.70) = 2.53, p = .014$. A planned contrast comparing HDE to all other videos was significant, $\beta = .10$, 95% CI: [.03, .16]. The same pattern of results emerged when using disclosure ratings as the DV for both the omnibus test, $F(10, 53.19) = 3.95, p < .001$ and planned contrast $\beta = .15$, 95% CI: [.10, .21]. Observed power, based on 1000 iterations, for the overall MLMs were .942 and .995, respectively.

Disclosure language and disclosure ratings positively correlated, $r(69) = .38, p < .001$, 95% CI: [.16, .57].

Discussion

Results indicate support for both hypotheses: disclosure language and disclosure ratings were both higher in videos in which content creators came out as LGBT than in their other videos and these two metrics were positively correlated.

Study 1b

To further investigate the linguistic markers of disclosure, we repeated study 1a with additional topics of self-disclosure: HIV and mental illness. Though the exact formula of *Authentic* is unpublished, the work on which it is based primarily relies on function words as

opposed to content and, thus, is blind to the actual topic of conversation. Because of this, we anticipated a similar pattern: that coming out videos would have higher levels of disclosure language and disclosure ratings than other videos and that these two measures would be correlated.

Method

The method for study 1b mimicked study 1a except using the search terms “coming out HIV” and “coming out depression” and “coming out anxiety” to assemble the corpus of transcripts, as well as a modification to self-disclosure ratings (described in the next paragraph). A total of 143 transcripts were collected across 17 content creators.

To reduce rater burden, transcripts were rated by a random two of the four original coders; interclass correlations accounting for random raters means (ICC2k; Shrout & Fleiss, 1979) indicate high inter-rater reliability, $r(139, 417) = .84$, $p < .001$, 95% CI: [.72, .89].

Results

Before running the analyses, we used the *simr* package (P Green & MacLeod, 2016) to complete a power analysis based on effects found in study 1a. Simulations for the overall disclosure language and ratings models suggested anticipated power of .973 and 1.000, respectively.

The linear mixed model in which videos were nested within creator within topic identified significant differences in disclosure language as a function of video, $F(10, 114.16) = 2.85$, $p < .01$. The planned contrast comparing HDE to all other videos was also significant, $\beta = .09$, 95% CI: [.05, .13]. The same pattern of results emerged when using disclosure ratings as the

DV for both the omnibus test, $F(10, 116.24) = 9.56, p < .001$, as well as the planned contrast, $\beta = .14, 95\% \text{ CI}: [.11, .18]$.¹

Disclosure language and disclosure ratings, again, positively correlated, $r(138) = .39, p < .001, 95\% \text{ CI}: [.24, .52]$.²

We then decided to run an exploratory analysis to test *Authentic* against other published models of text-based disclosure using all three disclosure topics. Barak and Gluck-Ofri (2007) propose using total word count (*WC*) and use of i-pronouns (*ipron*); Levi-Belz and Kreiner (2016) propose total word count, use of i-pronouns, and emotionality (*affect*). While all three models outperform a null model (chi square values range from 29.36 to 52.47, all p values $< .0001$), the model using only *Authentic* has better model fit than the others. See Table One for fit statistics.

Table One. Fit statistics for models predicting disclosure ratings across all three topics.

Name	LIWC Variables	AIC	BIC	Log Likelihood	$\Delta \chi^2$
(null)	none	359.42	369.47	-176.71	
(Barak & Gluck-Ofri, 2007)	<i>WC</i>	336.06	356.17	-162.03	29.36**
	<i>ipron</i>				
(Levi-Belz & Kreiner, 2016)	<i>WC</i>	333.50	356.96	-159.75	4.56*

¹ We also ran a model including all three topics which reflected the same pattern, $F(10, 178.67) = 4.20, p < .0001$. The planned contrast was significant, $\beta = .09, 95\% \text{ CI}: [.06, .12]$.

² Across all three topics the correlation between disclosure language and disclosure ratings remained significant, $r(209) = .38, p < .001, 95\% \text{ CI}: [.26, .49]$.

	<i>ipron</i>				
	<i>affect</i>				
(all)	<i>WC</i>	281.90	308.71	-132.95	53.60**
	<i>ipron</i>				
	<i>affect</i>				
	<i>Authentic</i>				
(Pennebaker et al., 2015)	<i>Authentic</i>	310.95	327.71	-150.74	52.47** ³

Note: * indicates $p < .05$, ** indicates $p < .001$; traditional guidance regarding fit statistics

prioritizes low AIC/BIC and high Log Likelihood values.

Discussion

These results further support those reported in study 1a: that while coders' ratings of self-disclosure are the gold-standard for assessing self-disclosure within the context of YouTube videos, the pattern remains strong when using an automated text analysis software. See Figure One.

³ Compared to null model.

Figure One. Standardized values of LIWC's *Authentic* variable compared to coders' ratings of disclosure across all video topics.

Study 2

Jourard and Laskow's (1958) early writing about disclosure introduces what they refer to as the dyadic effect – that disclosure begets disclosure. Altman and Taylor's (1973) Social Penetration Theory formalizes this process by reflecting on the tendency for members of a dyad to offer reciprocal self-disclosure. While audience members' relationships with content creators are not as dyadic as face-to-face relationships, the comment section of YouTube videos allows viewers to send messages to the content creator in the hopes that the creator might respond.

Additionally, due to the increased intimacy associated with disclosure and the tendency for audience members to more actively engage with content posted by those with whom they feel they have a close relationship (Gabriel et al., 2017; Perse & Rubin, 1989; A. M. Rubin et al., 1985), we anticipated a positive relationship between video disclosure and video meta-data. These meta-data are behavioral markers of the amount of interaction YouTubers are garnering on their videos.

We hypothesized a positive relationship between the amount of disclosure in the transcript of YouTube videos and the comments left on the videos. We also hypothesized that video authenticity should predict the number of views, comments, and likes that each video has, given that disclosure should enhance the relationship between audience members and the content creator (R. Rubin & McHugh, 1987).

Method

Data Collection

Using a JavaScript command line utility (Klostermann, 2017), we scraped (downloaded) all comments from the videos used in studies 1a and 1b. Within the weeks between studies some of these videos were removed, leading to a reduced sample. Additionally, some videos' comments could not be scraped, likely due to the high number of comments (between 69,000 and 169,000+ comments at the time of attempted scraping).⁴ A total of 1,230,322 comments were scraped from 216 videos (94.9% of the original videos).

Measures

Video Disclosure. LIWC-generated measures of *Authentic* used in studies 1a and 1b were retained for study 2.

Comment Disclosure. After being scraped, only comments (not replies to other comments) were passed through LIWC. All comments with a score of 0 on the *Dic* (a measure of the percentage of words in a text that are contained in LIWC's English dictionary) indicator were removed; this is a crude but effective way of removing comments made exclusively of graphics

⁴ Unfortunately, this affected HDE videos more so than non-HDE videos, specifically within the LGBT topic group. However, the number of comments metadata variable was unaffected.

(e.g., emojis) and many comments written in languages other than English. A total of 514,312 (41.8%) comments were retained. The median *Authentic* metric for each set of comments was used to reflect the amount of comment disclosure for each video.⁵

Video Meta-data. Meta-data were collected but remained unanalyzed during studies 1a and 1b. Number of views and number of comments were recorded exactly as they appeared on the video page while transcripts were being collected. Because of the way YouTube displays likes, any number over 1000 was estimated to the nearest hundreds place.

Results

A mixed-effect multi-level model in which video disclosure was used to predict comment disclosure with creator within topic indicated a significant effect, $F(1, 192.65) = 17.26$, $p < .001$, $\beta = .28$, 95% CI: [.15, .42].

Video disclosure also significantly positively predicted meta-data for both number of views, $F(1, 1186.1) = 3.95$, $p = .047$, $\beta = .12$, 95% CI: [.00, .24], as well as number of comments, $F(1, 195.84) = 4.36$, $p = .04$, $\beta = .14$, 95% CI: [.01, .26]. The relationship between video disclosure and likes was marginally significant in the anticipated direction, $F(1, 203.18) = 3.41$, $p = .067$, $\beta = .11$, 95% CI: [-.01, .22].

Discussion

These results support the relational aspect of disclosure that Jourard (1966) defines as the dyadic effect – that disclosure from one member of a dyad (in this case, video disclosure) is associated with disclosure from the other (average comment disclosure). Additionally,

⁵ Supplemental materials include the analysis run using the comments' mean scores which identify a similar pattern ($p < .001$), though attenuated due to extreme skew. Median values are not as sensitive to skew caused by our generous inclusion criteria of any comment with a *Dic* value > 0 .

disclosure is predictive of not only reciprocal disclosure, but other measures of audience engagement, including total number of views and comments. Given that YouTube's monetization structure is based heavily on audience engagement metrics (Han, 2018), these findings are important for content creators to keep in mind when planning their content.

General Discussion

Across two studies, results indicate that a metric generated from a word-count software moderately correlates with trained coders' ratings of disclosure and tracks the pattern anticipate in regard to HDE videos compared to creators' other videos. Though these patterns were stronger when measuring disclosure using raters (see Supplemental Materials), the goal of this paper was not to say that LIWC output should entirely replace content coding; instead we were interested in offering validation for the utility of LIWC's *Authentic* variable for predicting disclosure. While text analysis strategies are not perfect (see Boyd & Schwartz, 2020 for a history and critique of LIWC and related softwares), this strategy is a useful alternative when the number of texts to analyze is large. It took our trained coders weeks to complete their ratings for video transcripts; it took LIWC less than a minute to analyze transcripts and comments combined.

Though the quasi-experimental nature of these data make causal claims impossible, repeated time-series with reversal designs are some of the most robust designs for exploring associations when experimental manipulation is not an option (Miller et al., 2019). Multilevel modeling allowed us to isolate the effect of disclosure, controlling for repeated measures of video within different creators and topics of disclosure. Given that the data used are observations of publicly available information across different CSI groups posted over an 8-year

span (2012 to 2020), we argue that the patterns identified here reflect processes likely to be found in other videos and, possibly, other incidences of disclosure. Additionally, one of the strengths of this approach is the (anticipated) focus on function words as opposed to content words. This means that this LIWC indicator is blind to the disclosure being shared – it is based on *how* something is being shared more so than *what* is being shared. Of course, since the formula by which *Authentic* is calculated is not published, there may be some inclusion of content words. However, our analyses were consistent across video topic which makes this less of a concern.

On a related note: the careful reader of Table One may have noticed that, when comparing all models, the inclusion of all four predictors (*WC*, *ipron*, *affect*, *Authentic*) significantly improved model fit. Without knowing the process by which *Authentic* is calculated, we cannot endorse using this strategy to avoid potentially repetitive predictors. However, fit indices still outperformed other published models with just *Authentic* as a predictor.

Future research should expand on these findings by testing the same pattern on other forms of disclosure, ideally in a setting in which disclosure could be manipulated within speaker and about information other than CSIs. Working with social media data is challenging and there are no standard approaches to cleaning and screening assembled datasets (Stieglitz et al., 2018). We opted to use generous inclusion criteria and accounted for artifacts using modified measures of central tendency (using the median *Authentic* metric for comments as opposed to the mean); future research may use more stringent designs to further refine potential text-based metrics of self-disclosure.

The work aimed to validate the utility of a fast, broad, and easily-accessible metric for quantifying self-disclosure in transcripts and text. In addition to the known-groups paradigm helpful for establishing criterion validity (Hattie & Cooksey, 1984), we also demonstrated that this one-item metric was able to predict associated meta-data.

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