Affect-related Psychological Traits are Reflected by the Sentiment of Publicly Shared Text

Chulin Chen[1], Richard N. Landers[1], Ross Gore[2], and Elena M. Auer[1]

[1]University of Minnesota

[2]Old Dominion University

An increasing number of high-stakes decisions are now made based upon predictive models of publicly available sentiment data, especially on Twitter (Kwak et al., 2010). Sentiment is generally viewed as a desirable predictor in modeling various outcomes because of its simplicity of computation, its applicability regardless of text type, and its ability to reduce text into a single numerical summary value. What remains unclear is the degree to which sentiment reflects variance in psychological traits versus the situational context in which those traits were expressed. The goal of psychometric measurement is generally to standardize situational variance across measurement occasions so that this variance can be modelled as unsystematic error (Crocker & Algina, 1986). In doing so, the remaining variance is intended to be attributable to psychological characteristics alone (Crocker & Algina, 1986). Yet it is currently unknown to what degree and in what balance sentiment is influenced by trait versus situational causes.

The present study explored how a psychometric approach could be applied to sentiment data to draw conclusions about "latent trait sentiment" (L.T.S.), a term we use to describe the degree to which sentiment is consistent across contexts (i.e., regardless of topic, mood, or other nuisance situational causes) within a broader meaningful situational frame (e.g., a particular social media platform). This is in stark contrast to most sentiment research, in which human variation is considered error and thus the shared variance across people is targeted as theoretically interesting (Asur & Huberman, 2010; Jain, 2013). In the present study, we instead demonstrate that shared variance in sentiment within individuals across contexts can be treated as a meaningful individual difference variable.

H1: Shared variance of L.T.S. within individual across contexts can be modeled as a latent psychological trait.

To test whether L.T.S. is meaningfully associated with affect-related psychological traits, because sentiment and affect are so closely conceptually related, we also explored if positive (P.A.) and negative affect (N.A.) (Thompson, 2007), behavioral inhabitation (BIS) and activation (B.A.S.) (Carver & White, 1994), self-monitoring (Lennox & Wolfe, 1984), trait optimism (Scheier et al.,1994), big five personality (John et al., 1991), life satisfaction (Diener et al., 1985), and counterproductive work behavior (C.W.B.) (Koopmans et al., 2013) were associated with L.T.S.

RQ1: Is L.T.S. related to affect-related psychological trait variables?

Methods and Results

A total of 985 participants from Qualtrics's online sampling service and the University of Minnesota's undergraduate psychology participant pool with active Twitter accounts shared their Twitter handles with the researchers and completed study questionnaires. Of these, 842 were ultimately retained after data quality screening for multivariate outliers and invalid responses to directed response questions (Meade et al., 2012).

To classify tweets into categories representing different contexts, an algorithm was developed by first training a cross-validated Hierarchical Latent Dirichlet Allocation (hLDA) topic model using over 50,000 tweets collected from Twitter's API. This topic model's word distributions were then used as features to train a random forest classification model. The algorithm was applied to the Twitter timelines of our study subjects to classify individual tweets into four LDA topic clusters.

Positive and negative sentiments of each tweet were measured by an aggregate of established word emotion lexicons including N.R.C. (Mohammad & Turney, 2013), the general inquirer (Stone et al., 1966), and LIWC (Pennebaker et al., 2015). Averaged positive/negative sentiment for tweets classified into each topic cluster were computed for each individual.

C.F.A.s were conducted on positive/negative sentiment across the four topic clusters respectively to test Hypothesis 1. S.E.M.s in which positive/negative sentiment scores were regressed individually on each psychological variable were fitted to test Research Question 1.

The positive LTS CFA model is shown in Figure 1 ($\chi^2(2) = 33.10$, $p <.001$, CFI =.97, RMSEA = .14, SRMR = .03, omega = .80, AVE =.51). Apart from RMSEA and chi-squared, standards for all fit index were achieved, both composite reliability as measured by omega and validity as measured by AVE demonstrated satisfactory psychological properties. The negative LTS CFA model (Figure 2) showed good model fit, reliability, and validity ($\chi^2(2) = 5.09$, $p =.08$, CFI = 1.00, RMSEA = .04, SRMR = .01, omega = .82, AVE =.54). Hypothesis 1 was therefore supported. Results of individual models with psychological predictors and positive and negative sentiment were shown in Tables 1 and 2. Positive and negative sentiment could each be predicted by several affect-related variables.

Discussion

We demonstrate that psychometrically reliable and valid measures of L.T.S. can be created by employing topic modeling to create measurement occasions, treating the content of tweets as unsystematic measurement error, leaving only the stable trait component behind. We also show that stable affect-related psychological traits predicted variance in L.T.S. This suggest that word-level modeling holds potential for meaningful prediction of individual psychological traits. By using sentiment, the creation of a model with this level of prediction performance is possible even in reasonably small samples, unlike what has been demonstrated in previously published approaches which required more complex machine learning (i.e., Kosinski et al., 2013).

Drawing more accurate conclusions about individual psychological traits using sentiment can be applied in many contexts. By mathematically isolating L.T.S. and correcting for the bias it can introduce in between-subjects comparisons, researchers may be able to better predict affect-related outcomes like turnover or propensity for workplace violence. Similar benefits may apply in the broader situationally-focused machine learning literature. For example, unconsidered and relatively minor sample characteristics can negatively influence the accuracy of prediction (Tumasjan et al., 2010). By controlling for systematic error introduced by individual trait-level sentiment, adjusting for the L.T.S. of each person in a dataset before drawing between-persons conclusions, accuracy of prediction may be improved more broadly. A limitation of this study is difficulty with interpreting situations represented by topic clusters. However, our finding still supported consistency of sentiment across distinct contexts.

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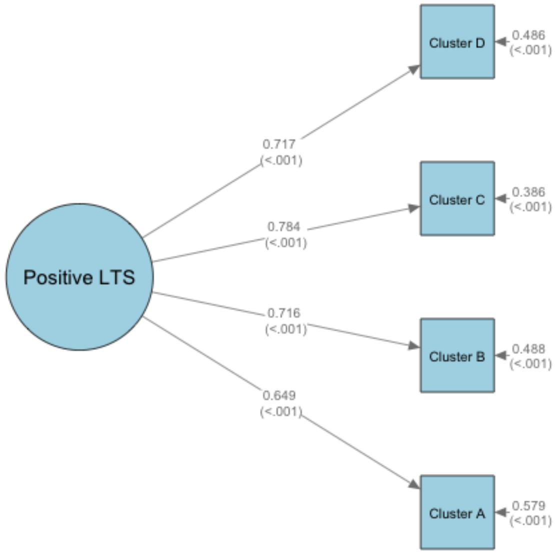

Figure 1. Confirmatory factor analysis for positive L.T.S., N = 842.

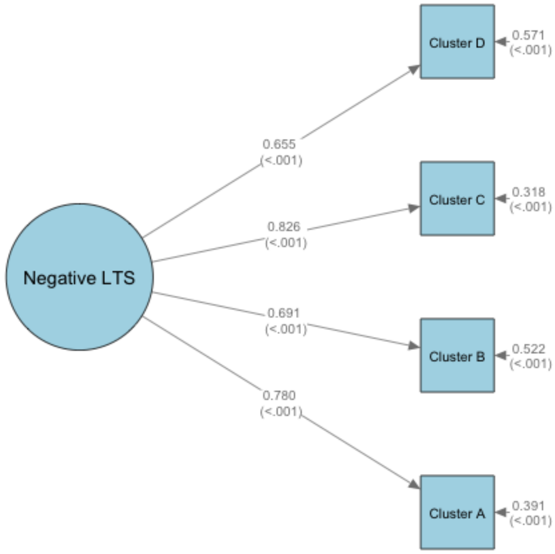

Figure 2. Confirmatory factor analysis for negative L.T.S., N = 842.

Table 1

Reliability of Psychological Constructs and Results of Individual Psychological Predictor and Positive Latent Trait Sentiment models.

Predictors	α	B	SD	Boot Lower	Boot Upper	χ^2	CFI	RMSEA	SRMR
PA	.89	.04	.05	-.06	.14	38.01***	.97	.09	.03
NA	.88	-.15**	.05	-.25	-.05	41.99***	.97	.09	.03
SM-EX	.80	.08	.05	-.01	.18	30.87***	.98	.08	.03
SM-SP	.79	.06	.05	-.03	.15	30.18***	.97	.09	.03
BAS_D	.74	.07	.06	-.05	.18	29.07***	.97	.09	.03
BAS_F	.68	.21***	.06	.10	.31	29.58***	.97	.09	.03
BAS_R	.70	.14	.10	-.07	.31	30.81***	.97	.09	.03
BIS	.56	.30***	.08	.16	.46	31.63***	.98	.08	.03
Optimism	.86	-.01	.04	-.08	.06	29.8***	.98	.08	.03
LS	.90	.08**	.02	.03	.12	29.43***	.98	.08	.02
CWB	.86	.15**	.05	.05	.25	32.37***	.98	.08	.03
BFI_E	.85	.08	.05	-.01	.18	37.78***	.97	.09	.03
BFI_A	.77	.07	.06	-.06	.20	40.9***	.97	.09	.03
BFI_C	.60	-.09	.09	-.28	.08	46.69***	.96	.10	.03
BFI_N	.87	.15***	.05	.05	.23	42.5***	.97	.09	.03
BFI_O	.76	-.27***	.08	-.43	-.13	38.1***	.97	.09	.03

Note. *PA is positive affect; NA is negative affect; SM-EX is self-monitoring; expressive behavior; SM-SP is self-monitoring, self-presentation; BAS_D is behavioral activation, drive; BIS is behavioral inhibition; LS is life satisfaction; CWB is counterproductive work behavior; BFI_E is extraversion; BFI_A is agreeableness; BFI_C is conscientiousness; BFI_N is neuroticism; BFI_O is openness to experience. □ is unstandardized regression coefficients of negative sentiment on individual psychological variables; SD is standard deviation of regression coefficient; Boot Lower is the lower bound of bootstrap interval for regression coefficients; Boot Upper is the upper bound of bootstrap interval for regression coefficients.*

χ^2is chi-squared statistics of the model. CFI is comparative fit index; RMSEA is root mean square error of approximation; SRMR is standardized root mean residual.

$*p < .05$. $**p < .01$. $***p < .001$.

Table 2

Reliability of Psychological Constructs and Results of Individual Psychological Predictor and Negative Latent Trait Sentiment models.

Predictors	α	B	SD	Boot Lower	Boot Upper	χ^2	CFI	RMSEA	SRMR
PA	.89	-.15**	.05	-.25	-.05	3.25	1	<.001	.01
NA	.88	.29***	.05	.20	.40	3.68	1	<.001	.01
SM-EX	.80	.03	.05	-.07	.12	7.08	1	.02	.01
SM-SP	.79	.11*	.05	.02	.22	6.74	1	.02	.01
BAS_D	.74	.13	.07	-.02	.25	5.64	1	.01	.01
BAS_F	.68	.22***	.07	.08	.36	3.29	1	<.001	.01
BAS_R	.70	.17	.11	-.03	.39	10.27	1	.04	.01
BIS	.56	.32***	.08	.16	.48	3.97	1	<.001	.01
Optimism	.86	-.19***	.04	-.27	-.12	5.00	1	.001	.01
LS	.90	-.08**	.03	-.13	-.03	5.26	1	<.001	.01
CWB	.86	.22***	.05	.12	.32	5.51	1	.01	.01
BFI_E	.85	-0.06	0.05	-0.14	0.04	2.83	1	<.001	.01
BFI_A	.77	-0.22***	0.07	-0.36	-0.09	4.16	1	<.001	.01
BFI_C	.60	-0.36***	0.08	-0.51	-0.21	8.59	1	.03	.02
BFI_N	.87	0.31***	0.05	0.22	0.4	4.76	1	.01	<.001
BFI_O	.76	-0.1	0.07	-0.24	0.04	6.992	1	.02	.02

Note. *PA is positive affect; NA is negative affect; SM-EX is self-monitoring; expressive behavior; SM-SP is self-monitoring, self-presentation; BAS_D is behavioral activation, drive; BIS is behavioral inhibition; LS is life satisfaction; CWB is counterproductive work behavior; BFI_E is extraversion; BFI_A is agreeableness; BFI_C is conscientiousness; BFI_N is neuroticism; BFI_O is openness to experience. □ is unstandardized regression coefficients of negative sentiment on individual psychological variables; SD is standard deviation of regression coefficient; Boot Lower is the lower bound of bootstrap interval for regression coefficients; Boot Upper is the upper bound of bootstrap interval for regression coefficients.*

χ^2is chi-squared statistics of the model. CFI is comparative fit index; RMSEA is root mean square error of approximation; SRMR is standardized root mean residual.

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.