You Write What You Are – Exploring the Relationship between Online Reviewers' Personality Traits and Their Reviewing Behavior

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Abstract. Online review system designers implement different design features to nudge their systems' users towards behaving in a certain way, e.g., by providing review templates to influence the content of reviews. Most of these measures apply to all users equally and do not take the individual reviewers' personality into account. Based on identified gaps within research on online reviews [1], as a first step to close one of these gaps, we present an exploratory study that reveals the relationship between personality traits and reviewing behavior. We analyze a comprehensive dataset of restaurant reviews from Yelp and determine the Big Five personality traits of each reviewer using IBM Watson. Amongst others, our results suggest that reviewers, who are rather extroverted, are less likely to write long reviews. These insights emphasize that design features should be developed with the reviewers' personality in mind and thus bear potential for future research.

Keywords: Online Review, Online Rating, Big Five, User Personality, Personality Traits

1 Introduction

Consumer experiences shared through online review systems reduce the information asymmetry between consumers and sellers [2, 3]. In other words, the information contained in reviews can help potential customers in making purchase decisions [3]. Review system providers can implement design features in their systems, i.e., through financial incentives [4], to nudge users towards a certain behavior [5]. Similarly, studies propose to implement review templates that nudge reviewers towards a certain review content (e.g., being critical or writing lengthier review texts, see 1 for an overview). However, the majority of studies on the design of online review systems considers features that are applied to all system users equally. Thus, the role of the individual user's personality (e.g., measured by the Big Five personality traits [6, 7]) in designing review systems has been widely neglected in the literature on online reviews, even though there is evidence that personality traits are important determinants of online behavior (e.g., on social media platforms) and that considering personality traits in design decisions (e.g., presenting user-specific recommendations) can significantly improve system performance (e.g., 8, 9). Understanding whether and

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how personality traits influence reviewing behavior is therefore crucial for designing personalized review systems but also for advertisers and businesses operating on review platforms since they could target consumers with specific personality traits. For instance, more open reviewer might write better reviews in terms of comprehensiveness and perceived helpfulness (by future potential customer), when they are provided with more flexible review template, where flexible means, that they can decide more independently how to structure the review and its look. To provide a first step towards achieving such an understanding, we aim to answer the following research question: *How are the reviewers' personality traits associated with the resulting reviews' ratings and number of words?*

2 Related Literature and Theoretical Background

The Big Five personality traits are an established theoretical grounding to describe a consumer's personality [6, 7]. *Extraversion* is associated with being sociable and outgoing. *Agreeableness* is described as being friendly and compassionate. *Conscientiousness* is associated with self-discipline and being organized. *Neuroticism* is described as being sensitive and susceptible to emotions. *Openness* is associated with being creative, curious and willing to try new things. These traits are associated with a set of bidirectional measurement scales verified in self and peer descriptions about a person's personality [7].

Building upon research on the Big Five traits, first studies began to analyze how personality traits affect electronic word-of-mouth (eWOM) (e.g., online reviews). For instance, eWOM in form of social media posts written by customers with stronger pronounced conscientiousness and openness tend to be more effective in terms of resulting purchase decisions [10]. Furthermore, it has been found that personality traits moderate the motivation to generate eWOM. For example, consumers with a high level of agreeableness are more likely to write a review due to altruistic reasons [11]. Based on these results, we argue that personality traits do not only influence the motivation to review and the effectiveness of reviews but also the reviewing behavior itself. For instance, reviewers with higher levels of openness should be more creative and thus might write longer reviews whereas neurotic reviewers might write shorter but more emotional reviews.

3 Empirical Analysis

We use review data from the yelp's 11^{th} dataset challenge consisting of review written about businesses (e.g., restaurants, dentists) in the US. In line with previous research, we use IBM Watson's Personal Insights Service[1] on all reviews of each reviewer in our dataset to identify personality traits [12, 13]. It bases on open-vocabulary approach which builds upon on a set of words matched with different manifestations

[1] https://cloud.ibm.com/docs/services/personality-insights?topic=personality-insights-science (Access: 30.10.2019)

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of personality traits [14]. It requires at least 100 words, but a higher number of words is recommended to provide more precise results. In regard to consistency studies with similar prediction models have found to be between 11% and 18% deviated from the actual big five values [15]. Therefore, we consider reviewers, who wrote between 313 and 1392 words. These values correspond to the 75th and 95th percentile regarding the number of words of all reviews from each reviewer. We choose the 95th percentile as upper bound to exclude outliers. We present the descriptive statistics of the main variables in Table 1. The upper six variables are on user-level and the last two variables refer to reviews. All 113,893 reviews considered are written by the 70,703 users.

Table 1. Descriptive Statistics

	Variable	N	Mean	Std. Dev.	Min	Max
User	*USER_WORDS*	70,703	797.274	303.619	313	1391
	OPENNESS	70,697	0.887	0.141	0.033	1
	EXTRAVERSION	70,697	0.545	0.282	0.000	0.999
	CONSCIENTIOUSNESS	70,697	0.703	0.238	0.000	0.999
	AGREEABLENESS	70,697	0.406	0.271	0.000	0.999
	NEUROTICISM	70,697	0.784	0.188	0.006	0.999
Rev	*REVIEW_WORDS*	113,893	155.983	136.805	4	1,051
	REVIEW_RATING	113,893	3.482	1.626	1	5

We included further information about the reviewers (e.g., number of friends), the businesses concerned by the review (e.g., average rating of prior reviews) and time variables. The Big Five are measured in percentiles based on a dataset from an IBM Watson study. We estimate the following equation:

$$Y_{ijrt} = \beta_0 + \alpha PERSONALITY_r + \beta_6\gamma_r + \beta_7\theta_{ijt} + \delta_j + \mu_t + \epsilon_{ijrt}$$

The term Y_{ijrt} describes our outcome variable (*REVIEW_WORDS*, *REVIEW_RATING*) of review i concerning business j written by reviewer r at time t as combination of a month and a year. The vector of $PERSONALITY_r$ contains the measurements of the reviewer's Big Five traits. The five coefficients contained in the vector α provide an estimate regarding how an increase in the percentile of a personality trait is associated with the respective outcome variable. We add further control variables to ensure that the estimates of these coefficients are not driven by other aspects. Since reviewer characteristics, such as the number of reviews a user has written, might be correlated with their personality traits and their reviewing behavior, we include a vector of reviewer characteristics γ_r. We also control for business characteristics. For instance, businesses offering a higher quality could be more likely to attract consumers with certain personalities. Therefore, we add a vector of business characteristics θ_{ijt} to control for observable and time-varying business characteristics as well as business-level fixed effects δ_j to capture time-constant heterogeneity. The

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vector μ_t represents time-level fixed effects whereas ϵ_{ijrt} represents the random unobservable error term.

Table 2. Preliminary Results (Ordinary Least Squares regression)

	(1)		(2)	
Dependent Variable	***REVIEW_WORDS***		***REVIEW_RATING***	
OPENNESS	0.507***	(0.051)	0.001***	(0.000)
EXTRAVERSION	-0.746***	(0.024)	0.005***	(0.000)
CONSCIENTIOUSNESS	0.010	(0.036)	0.001***	(0.000)
AGREEABLENESS	-0.273	(0.023)	0.001***	(0.000)
NEUROTICISM	0.111**	(0.047)	-0.001*	(0.000)
N	113,885		113,885	
Note: Robust standard errors in parentheses. *<p.1; **<p.05; ***<p.01; Control variables: reviewer-specific, review-specific, business-specific, business- and time-fixed effects				

Table 2 presents our preliminary results. Column (1) describes the estimated coefficients for our model with *REVIEW_WORDS* as a dependent variable. Our results suggest significant differences in the length of reviews depending on the reviewers' personality traits. For instance, an increase in the openness of a reviewer by 1 percentile is associated with an increase in review length by 0.51 words. In other words, we would expect that reviewers in the 75th percentile write on average 25 words more when compared to reviewers in the 25th percentile of openness. Note, that the reviews consist of about 155 words on average. Column (2) presents the results with *REVIEW_RATING* as a dependent variable. Our results indicate that reviewers in the 100th percentile give about 0.5 more stars when compared to reviewers in the 1th percentile of extraversion.

4 Conclusion and Further Steps

Developing design features in review systems with the intent to nudge reviewers requires a deep understanding of how a reviewer's personality traits affect reviewing behavior. This research-in-progress presents a first exploratory study that helps with building this understanding. We plan to extend this research-in-progress in two major ways. First, we plan to further develop this study by considering additional dependent variables such as readability or perceived usefulness. Second, we plan to conduct experiments to (1) investigate the internal validity of our results and (2) analyze the impact of different design features (e.g., different types of review templates) in the light of the participants' personality traits. This comprehensive research program could then guide practitioners and researchers in developing design features for review systems that take their users' individual personality into account.

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