2017

Literary Theory within a Cross-Classified Multilevel Framework: Personality Similarity between Writers and Readers Predicts Reader Inspiration

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BA Economics,
North Carolina State University, 2013

A Thesis presented to the Graduate Faculty of
The College of William & Mary in Candidacy for the
Degree of Master of Arts

Department of Psychology

College of William & Mary
August, 2017

APPROVAL PAGE

Thesis is submitted in partial fulfillment
of the requirements for the
degree of Master of Arts

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Approved by the Committee, June, 2017

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COMPLIANCE PAGE

Research approved by

Protection of Human Subjects Committee

Protocol number(s): PSYCHIRC-20051005-0-tmthra
Personality and the Writing Process

PHSC-2010-01-25-6450-tmthra
Responses to Poetry (version 2)

Date(s) of approval: 2005-10-08 through 2006-10-08

2010-01-29 through 2011-01-29

ABSTRACT

Literary theorists have pointed to a relationship between writer-reader personality similarity and better outcomes in the reader. Furthermore, there is empirical evidence indicating that personality similarity between two individuals leads to positive outcomes. We[1] tested the hypothesis that personality similarity between writers and readers predicts greater inspiration in the reader. Our results supported this hypothesis. Profile similarity (i.e., similarity of Big Five trait profile) between writers and readers predicted greater reader inspiration. Single-trait similarity (i.e., similarity of single Big Five traits) between writers and readers predicted greater reader inspiration. These findings are noteworthy because we show that the scientific method can be leveraged to test the verisimilitude of a literary theory, which has not been possible using the current methods of literary criticism.

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ACKNOWLEDGEMENTS

This writer wishes to express his appreciation to Professor Todd Thrash, under whose guidance this investigation was conducted, for his patience, guidance, and criticism throughout the investigation. The author is also indebted to Professors John Nezlek and Chris Conway for their careful reading and criticism of the manuscript.

The writer also wishes to express gratitude for the unwavering support of his parents, Byron and Kathleen, and the welcomed levity of his brother, Ben.

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> “The interests of a writer and the interests of his readers are never the same and if, on occasion, they happen to coincide, this is a lucky accident.”
> - W. H. Auden (1962)

W. H. Auden theorized about the nature of outcomes when writers’ interests and readers’ interests overlapped; he declared that these events were “lucky accident[s]”. In doing so, he suggested that these outcomes were infrequent, due to chance, and positive in nature. Although Auden’s proposition has face validity, such that a reader may serendipitously discover a writer whose text is inspiring, his claim is difficult to evaluate with literary theory alone. Literary theorists have used philosophical inquiry, historical reference, and linguistic analysis, among other techniques to theorize about positive outcomes in readers. These methods, however, make it difficult for critics to examine the validity of theories – whether one literary theory has greater verisimilitude than another theory. We propose that the scientific method – a useful framework in which researchers can rigorously evaluate theoretical claims with empirical methods – be used as a technique for examining literary theories. In the current study, we employ the scientific method by using laboratory procedures and statistical techniques to test what Auden referred to as a “lucky accident”. Namely, our goal is to test whether similarity between writers and readers leads to positive reader responses. In the following, we highlight the sparse bits of relevant theory and empirical evidence to support our hypothesis.

Theoretical support for our similarity hypothesis originates in part from a school of literary criticism known as reader-response theory. Adherents of reader-response theory are interested in how readers make meaning from a text

(Tyson, 1999). Instead of analyzing the features of a text itself, reader-response theorists study the dynamic process of engaging with the text. For instance, Iser (1974) argued that it is the convergence of a text and a reader that brings a work into existence. The dynamic nature of a text cannot be solely contained within the text or the disposition of the reader, but in the interplay between both. Additionally, Fish (1970) suggested that there is both a general reader response and an idiosyncratic reader response. The general reader response is attributable to readers' "linguistic competence" (Fish, 1970, p. 83) of a text. Readers have similar responses to a text because they share a set of linguistic rules that allows for uniform interpretation. Simultaneously, each reader responds to a text in a unique way depending on their interests, their dispositions, and the interplay between their characteristics and writers' characteristics. This idiosyncratic response allows for "the fact that completely different readers can be differently affected by the 'reality' of a particular text" (Iser, 1974, p. 278).

We propose that Fish's (1970) general-idiosyncratic conceptualization of reader response may be refined by reference to the statistical technique of variance decomposition in a basic analysis of variance (ANOVA) framework. In brief, ANOVA allows researchers to statistically examine the effect of one or more independent variables on a dependent variable. We have two independent variables of interest in the current study – the writer and the reader, and one dependent variable – a positive reader response. There are three separate effects to note. First, there may be a main effect of writer, such that there is something about the writers, the text, or the writing process that affects response in a typical reader. We posit that this main effect of writer conceptually maps onto Fish's general reader response component. There is a uniform quality about the text, whether it is the disposition of the author, the linguistic features he or she uses, or the common understanding of readers (i.e., "linguistic competence", Fish, 1970, p. 83) that elicits a general reader response. Second, there may be a main effect of reader, suggesting that there is something about the readers or the reading process that affects readers' responses to a typical text. While there may be an average reaction among readers to a text, these same readers may also interpret the same text in different ways. Third, there may also be a writer by reader interaction effect, such that there is a unique pairing of a writer variable and a reader variable that affects reader responses. We propose that Fish's idiosyncratic reader response component is a blend of the main effect of reader and the interaction effect between writer and reader. It is possible that readers respond to a text in different ways depending on their dispositions, while it is also possible that readers respond to a text in different ways depending on unique connections between particular writers and particular readers. It is this interaction effect that we are centrally concerned with in the current study: Does greater similarity between a given writer and a given reader lead to a better outcome in the reader?

In the next section, we examine a reader response that is theoretically relevant to writer-reader similarity and can be tested using empirical methods.

Reader Response - Inspiration

There are a variety of reader responses that can be examined in the broad context of writing and reading. It is beyond the scope of this article to test all possibilities. Therefore, our imperative is to examine a reader response that is theoretically plausible and empirically testable. Given that literary theorists typically analyze creative texts, we aim to study a reader response relevant to creative writing (i.e., poetry). In effect, we bring forth inspiration in the reader as a plausible reader response. Inspiration is a theoretically relevant reader response because it has undergone a revival in both literary theory and psychological science. For example, the poet Paul Valéry (1958) argued that inspiration in the reader is the primary objective of the poet. Clark (1997) found that inspiration is “the oldest and most contemporary theory of the genesis of the poetic” (p. 282).

In psychology, Thrash and Elliot (2003, 2004) provided a tripartite conceptualization of inspiration that is domain-general and can be used across a variety of disciplines (e.g., literary criticism, psychology, theology). The researchers argued for three defining characteristics of inspiration: evocation, transcendence, and approach motivation. That is, inspiration is *evoked*, such that a stimulus arises from the environment or from an intrapsychic source (e.g., memory). The individual recognizes the stimulus for its epistemic value, which *transcends* an individual’s ordinary outlook into new or better possibilities. Finally, these possibilities may be acted out through *approach motivation,* a type of motivation that moves one to pursue positive outcomes rather than to avoid negative outcomes. These three defining features characterize inspiration regardless of context, whether creative, spiritual, or interpersonal. We examine reader inspiration in the context of writing and reading because it is directly relevant to reader responses; readers may be inspired to pursue creative endeavors, spiritual discovery, or other forms of inspiration after reading a creative text.

In the context of writing, the tripartite definition of inspiration amounts to the description given by Thrash, Maruskin, Cassidy, Fryer, and Ryan (2010): Creative inspiration is “a motivational state that is evoked in response to getting a creative idea and that compels the individual to transform the creative idea into a creative product.” The researchers showed that inspiration statistically mediates the relationship between a creative idea and a creative product in a variety of writing domains: poetry, fiction, and science. In other words, inspiration functions as a transmitter of a creative idea into a creative product. Related research has shown that greater writer inspiration leads to greater reader inspiration (Thrash, Maruskin, Moldovan, Oleynick, & Belzak, 2016). This effect was moderated by readers’ openness to experience, such that readers who were higher in openness to experience were more likely to be inspired when writers were inspired. These results show that inspiration is both a theoretically relevant reader response and a testable psychological construct.

We turn next to the topic of similarity between writers and readers. Auden wrote that a convergence of interests between a writer and reader, however infrequent, resulted in positive outcomes. Overlapping interests may be one of many relevant personal characteristics in explaining positive reader responses. In the current study, however, we propose that a convergence of personality traits between a writer and a reader is also important in explaining a positive response in the reader. We argue that personality traits may better capture the full breadth of individual differences in a parsimonious way. Thus, we test whether greater personality similarity between a writer and a reader will yield greater inspiration in the reader. In the following, we present evidence showing that personality similarity between two individuals generally leads to positive outcomes.

Personality Similarity Outcomes

Personality similarity between two individuals has seldom been studied in the context of writing and reading. Yet, personality similarity between two individuals has been examined in recent years in other domains, including martial and couple satisfaction (Luo & Klohnen, 2005; Gaunt, 2006), interpersonal attraction (Montoya, Horton, & Kirchner, 2008), organizational relationships (Schaubroeck & Lam, 2002), and business negotiations (Wilson, DeRue, Matta, Howe, & Conlon, 2016). In each of these domains, the consensus is that greater personality similarity between two individuals is linked to positive outcomes. For instance, Luo and Klohnen (2005) showed that there was a positive relationship between personality similarity of couples and marital quality. This effect was significant and robust in both husbands and wives for personality traits, but not for attitudinal characteristics (i.e., values, political attitudes, religiosity). Gaunt (2006) reported that greater personality similarity was associated with higher levels of marital satisfaction and lower levels of negative affect. Montoya et al. (2008) found that greater personality similarity in acquaintances led to more interpersonal attraction. A caveat to this finding was that the effect of similarity on interpersonal attraction in friendships diminished as time knowing one another increased; in other words, the effect was not significant in existing friendships. In organizational relationships, Schaubroeck and Lam (2002) showed that individuals were more likely to be promoted if they were similar in personality to their peers while working a highly individualistic setting. Supervisor-subordinate personality similarity predicted more promotions in highly collectivistic work settings. Wilson et al. (2016) found that negotiators who were more similar on both agreeableness and extraversion (i.e., similarly high or low on both traits) were more likely to show positive emotional displays and tended to reach agreements faster. Thus, there is evidence that personality similarity in a variety of contexts is related to positive outcomes.

Having provided theoretical support for the effect of personality similarity on positive outcomes, we turn next to research focused on the personality of the writer.

Personality in Writing

One of the first to analyze personality in writing was Pennebaker and King (1999). These researchers found that writers' linguistic styles and their use of words are meaningfully related to writers' personality traits. They developed text analysis software called the Linguistic Inquiry and Word Count (LIWC), which places used words into broad categories, such as language composition, psychological processes (i.e., emotional, cognitive, and social), and current concerns. Within these broad categories are more specific language-use categories, including first-person singular pronouns, articles, words of more than

6 letters, and positive and negative emotion words. Pennebaker and King found that these language-use categories were modestly correlated with the Big Five personality traits (Costa & McCrae, 1992a). For instance, neuroticism correlated positively with negative emotion words ($r = .16$), while extraversion correlated positively with positive emotion words ($r = .15$). Moreover, openness to experience was positively related to words of more than 6 letters ($r = .16$) and negatively related with first-person singular pronouns ($r = -.13$) and present tense verbs ($r = -.15$). Language-use correlations were also found for neuroticism and conscientiousness.

A number of researchers have extended the work of Pennebaker and King. Hirsh and Peterson (2009) found modest to moderate correlations between language-use categories and facets of the Big Five ($|r| = .19 - .40$). Fast and Funder (2008) showed that word use is correlated with self-reported and acquaintance-reported personality ratings and behavior. Yarkoni (2010) conducted a large-scale analysis with nearly 700 blogs and found that most LIWC categories were modestly related to personality variables. Qiu, Lin, Ramsay, and Yang (2012) found that, on microblogging websites like Twitter, observers relied on certain linguistic cues for making personality judgements. Together, these studies provide strong empirical support for a link between personality and writing. Although the effect sizes were modest by conventional standards (Cohen, 1988), the evidence indicates that a writer's personality is manifested in the words he or she uses.

Writer-Reader Personality Similarity

Despite the established link between personality and writing, the link between writer and reader personality has not been clearly established. This is in large part due to a dearth of research on personality similarity between writers and readers. An exception to this is work by Li and Chignell (2010).

Li and Chignell (2010), who studied writing and reading in the context of blogging and e-communication, found that readers were more attracted to writers who were *perceived* to be similar to them in personality, but were not necessarily attracted to those writers who were *actually* similar (Li & Chignell, 2010). The readers tended to agree on the personalities of writers based on linguistic cues from the blogs. The readers' judgements of writers' personalities, however, did not always match the actual writers' personalities. This null result for actual similarity is noteworthy because it is does not support our hypothesis that writer-reader similarity leads to greater reader inspiration. We note, however, that this study had a major limitation. Li and Chignell used a very small sample size consisting of 8 writers and 12 readers. If the effect size is modest in the population, power in finding such an effect was indubitably low in their study. Thus, the question of whether actual writer-reader personality similarity predicts greater reader inspiration remains unanswered.

Having introduced theory and findings relevant to our hypothesis, we next discuss analytical considerations and methods for testing whether personality similarity leads to greater reader inspiration. We begin by operationalizing personality similarity in two different ways. First, personality similarity may be operationalized by using profiles, such that writers and readers are similar on a configuration of theoretically cohesive variables (i.e., Big Five trait profile). Second, personality similarity can be operationalized by using single traits (i.e., individual Big Five traits). Writers and readers may be similar on individual traits, and similarity on these traits may lead to greater reader inspiration. In the last section before the results, we formally state the hypotheses.

Analytical Considerations

Profile Similarity

There are some key considerations involved with measuring similarity between two individuals. One important consideration concerns the set of variables used to define similarity between individuals. A researcher must operationalize similarity between two individuals based on theory and the research question at hand. Another consideration concerns measurement. A variety of measures have been developed to quantify profile similarity, and it is important to use a valid index. In the following, we provide theory and arguments for both considerations.

Operationalizing profile similarity. In the current study, we define profile similarity in terms of the Big Five personality framework, which includes agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience (Costa & McCrae, 1992a). Researchers have shown that personality is related to a wide variety of emotional, behavioral, and cognitive outcomes. For example, extraversion predicts greater positive affect (Fleeson, Malanos, & Achille, 2002), conscientiousness predicts higher college grades (McAbee & Oswald, 2013), and openness to experience predicts more creativity and divergent thinking (McCrae, 1987). The Big Five trait theory (McCrae & Costa, 1999) has been one of the most broadly used theories of personality structure in modern psychological science. Other theories of personality structure include the HEXACO trait model (Ashton & Lee, 2007), as well those found in the motivation literature, such as approach and avoidance temperaments (Elliot & Thrash, 2002). The HEXACO model builds on the Big Five by adding a dimension of Honesty and Humility, while the approach and avoidance temperaments map on to the extraversion and neuroticism dimensions of the Big Five. We concluded that the Big Five inventory afforded the most parsimonious coverage for measuring personality similarity in writers and readers. In addition to adequate coverage of similarity, researchers have found modest, yet consistent correlations between language use and all Big Five personality traits (Pennebaker & King, 1999; Yarkoni, 2010). By using the Big Five model to measure personality similarity between writers and readers, we may also extend the findings of previous research in a scientifically useful way.

Measuring profile similarity. Multiple indices of profile similarity have been developed and used in dyadic research since the 1930s. Candidate indices include correlations (Burt, 1937; Cohen, 1969), distance metrics (Cattel, 1949; Cronbach & Gleser, 1953), and distinctive profile similarity (Furr, 2008). It is important to identify an index that is valid and theoretically defensible for the current study. The following discussion provides arguments for operationalizing writer-reader profile similarity in terms of distinctive profile similarity.

Pearson’s correlation was one of the first indices to be used in similarity research. Instead of correlating variables among a group of individuals, as is typical when using a correlation, Burt (1937) proposed correlating individuals among a group of variables. For instance, in the current study, profiles are comprised of the Big Five traits. In effect, five cases of data (i.e., five traits) would be used to compute a correlation between two individuals. Correlating individuals provides an index that ranges from +1 to -1 and measures “shape” similarity. For example, if person A and person B were both higher on extraversion than on neuroticism and both higher on conscientiousness than openness to experience, these individuals would likely have high shape similarity. Although a correlation across a set of traits (i.e., between individuals) provides an intuitive and easily computed index for profile similarity, some researchers have noted that it does not take into consideration mean differences between profiles (i.e., “elevation”) or differences in variability between profiles (i.e., “scatter”). For instance, if person A scored high in many traits, while person B scored low in many traits, these individuals would have different elevations. Furthermore, if person A scored far from his or her mean on many traits, while person B scored close to his or her mean on many traits, these individuals would have different scatter. Therefore, correlations may only capture the extent to which two individuals are higher or lower on a particular variable relative to another variable (i.e., shape similarity).

Distance measures, like the one provided by Cronbach and Gleser (1953), have been proposed to address this presumed shortcoming of profile correlations. By determining the Euclidean distance between corresponding variables on two profiles, distance measures have been proposed to account for profile differences in shape, elevation, and scatter. But despite the supposed deficiency of correlating persons, and therefore using distance measures to account for elevation and scatter differences, distance measures do not in fact correct for profile elevation.

Cohen (1969) showed that profile correlations (and profile elevations) are affected by an arbitrary direction of scaling in the profile elements. For example, a researcher can either score an extraversion-introversion trait variable with a high score indicating extraversion and a low score indicating introversion, or a high score indicating introversion and a low score indicating extraversion. The direction of scaling does not affect the factor structure (Tellegen, 1965), but does affect profile correlations. Cohen provided a remediation for this problem, which involves reflecting the variables in a profile, appending these reflected scores to each profile, and correlating individuals using both the original variables and the reflected variables. To illustrate, each profile originally consisted of five cases since we used the Big Five inventory. With Cohen's remediation, each profile would now consist of 10 cases; five cases are the original Big Five trait scores and five cases are the reflected Big Five trait scores. These profiles of 10 cases are then correlated with other individuals' profiles to yield correlations that do not change due to the arbitrary scaling of variables. Since Cohen drew attention to this scaling problem, another observation can be made as it relates to the concept of elevation – a component of profiles that distance measures supposedly account for. If a researcher can arbitrarily scale a variable high or low, then the elevation differences between profiles are not inherent to the profiles. In other words, profile elevation is dependent on the arbitrary direction of scaling. Therefore, distance measures do not provide any more information about profile similarity than what correlations provide.

We have noted the specious solution of using distance measures to account for profile elevation and scatter. We have also highlighted a real problem with using profile correlations as an index of profile similarity. That is, the direction of scaling a trait can cause large discrepancies in profile correlations. To correct for this problem, Cohen (1969) provided a remediation. But there is another problem with using profile correlations: profile correlations are confounded by normativity (Cronbach, 1955; Furr, 2008).

Researchers have found that two random profiles are likely to be positively correlated because (1) both profiles reflect elements of their group's average profiles, and (2) the average profiles across groups are likely to be similar. This problem has been deemed the normativity problem: similarity between individuals may not be due to actual similarity, but rather due to an artifact of individuals being similar to the group average and group averages being similar to each other. Additionally, normativity has been found to be a proxy for socially desirable responses (Wood & Furr, 2016), suggesting that group similarity (i.e., normativity) may confound profile similarity between two individuals. To prevent confounding of similarity between profiles, Furr (2008) recommended removing normativity from each profile. This is accomplished by first subtracting the average group profile from each individual's observed profile. The resulting profile indicates the ways in which an individual differs from the average profile.

This mean-centered profile is called a distinctive profile. Second, a researcher correlates distinctive profiles to determine the extent to which individuals differ from the average profile in similar ways. For example, if two individuals were both much higher than average on extraversion and conscientiousness and slightly lower than average on neuroticism and openness, their distinctive profile similarity correlation would be strong and positive.

In addition to removing normativity, Furr (2008) showed that an overall profile similarity correlation (i.e., correlating observed-score profiles) may be algebraically decomposed into a distinctive profile correlation and other correlations of possible theoretical use. Furr's Model 2 was of theoretical interest in our writer-reader framework because it decomposed overall profile similarity into a distinctive similarity correlation, a constant term across all profiles, and two cross-profile correlations. In our writer × reader context, the cross-profile correlations included writer normativity – the extent to which a writer is similar to the average reader, and reader normativity – the extent to which a reader is similar to the average writer (see Furr, 2008, Model 2 decomposition). Writer normativity may be particularly important for reader inspiration because a writer may appeal to a wide reader base because he or she is similar to the average reader. Reader normativity may also be important for reader inspiration because a given reader may connect to a common thread present among the average writer (e.g., writer intent) because he or she is similar to the average writer. Thus, testing these additional variables provide a valuable level of investigation for the current study.

Our review suggests that combining Furr's (2008) Model 2 decomposition approach with Cohen's (1969) scaling remediation provides the most defensible index to test our hypothesis. Figure 1 shows an illustration of these indexing methods. We turn next to similarity between individuals on single traits.

Observed Personality Profile			Normative Personality Profile		Distinctive Personality Profile
Writer A			*(constant across writers)*		
Agreeableness	2	-	4.00	=	-2.00
Conscientiousness	4	-	3.50	=	-0.50
Extraversion	5	-	3.75	=	1.25
Neuroticism	3	-	2.00	=	1.00
Openness to Experience	4	-	3.00	=	1.00
Agreeableness (R)	4	-	2.00	=	2.00
Conscientiousness (R)	2	-	2.50	=	0.50
Extraversion (R)	1	-	2.25	=	-1.25
Neuroticism (R)	3	-	4.00	=	-1.00
Openness to Experience (R)	2	-	3.00	=	-1.00
Reader B			*(constant across readers)*		
Agreeableness	4	-	4.25	=	-0.25
Conscientiousness	5	-	3.75	=	1.25
Extraversion	2	-	4.00	=	-2.00
Neuroticism	1	-	1.50	=	-0.50
Openness to Experience	2	-	2.50	=	-0.50
Agreeableness (R)	2	-	1.75	=	0.25
Conscientiousness (R)	1	-	2.25	=	-1.25
Extraversion (R)	4	-	2.00	=	2.00
Neuroticism (R)	5	-	4.50	=	-0.50
Openness to Experience (R)	4	-	3.50	=	0.50
Distinctive Similarity *(distinctive profile correlation between writer A and reader B)*				=	-0.45
Writer Normativity *(correlation between writer A observed profile and reader normative profile)*				=	-0.55
Reader Normativity *(correlation between reader B observed profile and writer normative profile)*				=	-0.27

Figure 1. Two example distinctive profiles for a writer and reader with Cohen's (1969) remediation.

Single-Trait Similarity

In addition to profile similarity, we examined single-trait similarity, or how similarity between writers and readers on a particular trait (e.g., extraversion) predicts greater reader inspiration. Examining similarity of particular traits provides a related, but different level of analysis for the study. On one hand, testing the effects of profile similarity and single-trait similarity on reader inspiration are intertwined just by virtue of involving the same Big Five traits. On the other hand, profile similarity and single-trait similarity test different hypotheses. Profile similarity concerns whether the writer and reader have similar configurations of traits and therefore is a person-focused concept rather than a variable-focused concept. Nevertheless, it is also important to examine similarity of particular traits because similarity may be less beneficial for some traits than others. For instance, Thrash and Elliot (2003) argued and found that openness to experience and extraversion are conducive to inspiration. It is possible that being high in these particular traits, rather than being similar to the writer on these traits, is conducive to maximal reader inspiration. Therefore, it is possible that openness to experience and extraversion may show weaker similarity effects on the reader. In the following, we discuss our method for testing the effect of single-trait similarity on reader inspiration.

Measuring single-trait similarity. We looked to the congruence literature in organizational research to identify a valid method for measuring congruence (i.e., similarity) on single personality traits and testing the effects of single-trait similarity on reader inspiration. Many studies in organizational research have used difference scores to measure congruence or similarity between managers and subordinates. These difference scores are then used to predict outcomes of theoretical interest. Despite the prevalence of difference scores in research, there has been mounting criticism of their use for multiple reasons (Edwards, 2001; Edwards & Parry, 1993). These reasons include (1) conceptual ambiguity in using a measure composed of two components, (2) constraining the coefficient of both components of a difference score to be equal and negative of one another without theoretical or empirical support, and (3) the insidious influence of component variances on difference scores (see Edwards, 2001, for details).

The proposed alternative to using difference scores in congruence or similarity research is polynomial regression and response surface methodology (Edwards & Parry, 1993). Polynomial regression allows us to properly model the three-dimensional relationship between a writer trait, a corresponding reader trait, and reader inspiration. To capture non-linear relationships between these three variables, higher-order terms for each trait (i.e., quadratic, cubic, etc.), in addition to a product term between a writer trait and a corresponding reader trait, are included into a regression model. These additional terms in the model allow for a three-dimensional graphical representation (e.g., saddle-shaped) of the effect of single-trait similarity on reader inspiration. Also, response surface methodology provides a set of procedures to formally test similarity hypotheses. For instance, if a researcher hypothesizes that an outcome variable (e.g., reader inspiration) will be maximized when two individuals have the same score on two corresponding variables (e.g., writer extraversion and reader extraversion), then the surface of the polynomial model should be greatest at the line $y = x$.

Edwards (1995) provided a systematic strategy for determining whether a model should incorporate higher-order terms and whether to formally test surface features of the model. There are four conditions that must be met to support a polynomial model. First, the variance explained by the equation should significantly differ from zero. Second, the coefficients should follow the appropriate pattern, such that coefficients differ significantly from zero and have the expected signs. Third, the constraints corresponding to the model should be satisfied. Lastly, the variance explained by the set of terms one order higher than those in the equation should equal zero. If these four conditions are met, the researcher may conclude support for the polynomial model and proceed to test for similarity effects using response surface methodology. If these four conditions are not met, the researcher may not conclude support for the polynomial model.

Edwards (2002) also distinguished between an exploratory approach and a confirmatory approach. For an exploratory approach, no model is specified a priori. Instead the researcher estimates regression equations with increasingly higher powers (i.e., linear, quadratic, cubic, etc.) included in the model until one or more of the four conditions is not met. For a confirmatory approach, the researcher specifies an a priori polynomial model based on previous research or the hypothesis being tested. A researcher may specify a quadratic polynomial model without building up from lower order models by using a confirmatory approach. Edwards (2002) recommended specifying an a priori model if the goal is to test for congruence (i.e., similarity) and the effects of congruence on an outcome variable. Thus, we took a confirmatory approach with the current analyses and specified a quadratic (second order) polynomial model to test the effects of single-trait similarity on reader inspiration. That is, for each Big Five trait we specified a quadratic polynomial model[2].

Data Structure

In the current study, we combined two datasets used in previously published studies. In the first study, 195 student writers wrote a poem about the human condition (Study 3, Thrash et al., 2010). In the second study, 220 student readers read each poem from Thrash et al., (2010) and responded using self-report questionnaires (Thrash et al., 2016). Consistent with Thrash et al. (2016), we crossed the 195 student writers with the 220 student readers to produce a writer × reader data matrix as shown in Figure 2. There were 42,900 possible writer × reader observations. The writer × reader data matrix in Figure 2 shows that each cell includes one observation per outcome: for example, reader 1 inspiration in response to the poem of writer 1. Each row in the data matrix is populated by a writer and their poem, while each column is populated by a reader. Crossing a writer with a reader results in a writer × reader cell observation (i.e., reader inspiration). This unique data structure creates various statistical challenges.

One statistical challenge is the nesting structure that results when crossing writers with readers. To illustrate, any given writer’s text was read by every reader (missing data aside). Different readers’ responses to the same text cannot be considered independent of one another. Thus, responses are nested within writers’ texts. Additionally, all writers’ texts were read by any given reader. Since a reader may respond to all texts in a similar way, his or her responses also cannot be considered independent of one another. Thus, responses are also nested within readers.

We have two nesting structures that exist within one dataset. To account for these crossed dimensions, in which responses are dually nested within both writers' poems and readers, we must use a special case of multilevel modeling called cross-classified multilevel modeling (Raudenbush & Bryk, 2002). Cross-classified multilevel modeling properly models the error structure resulting from multiple dimensions of nesting within a dataset.

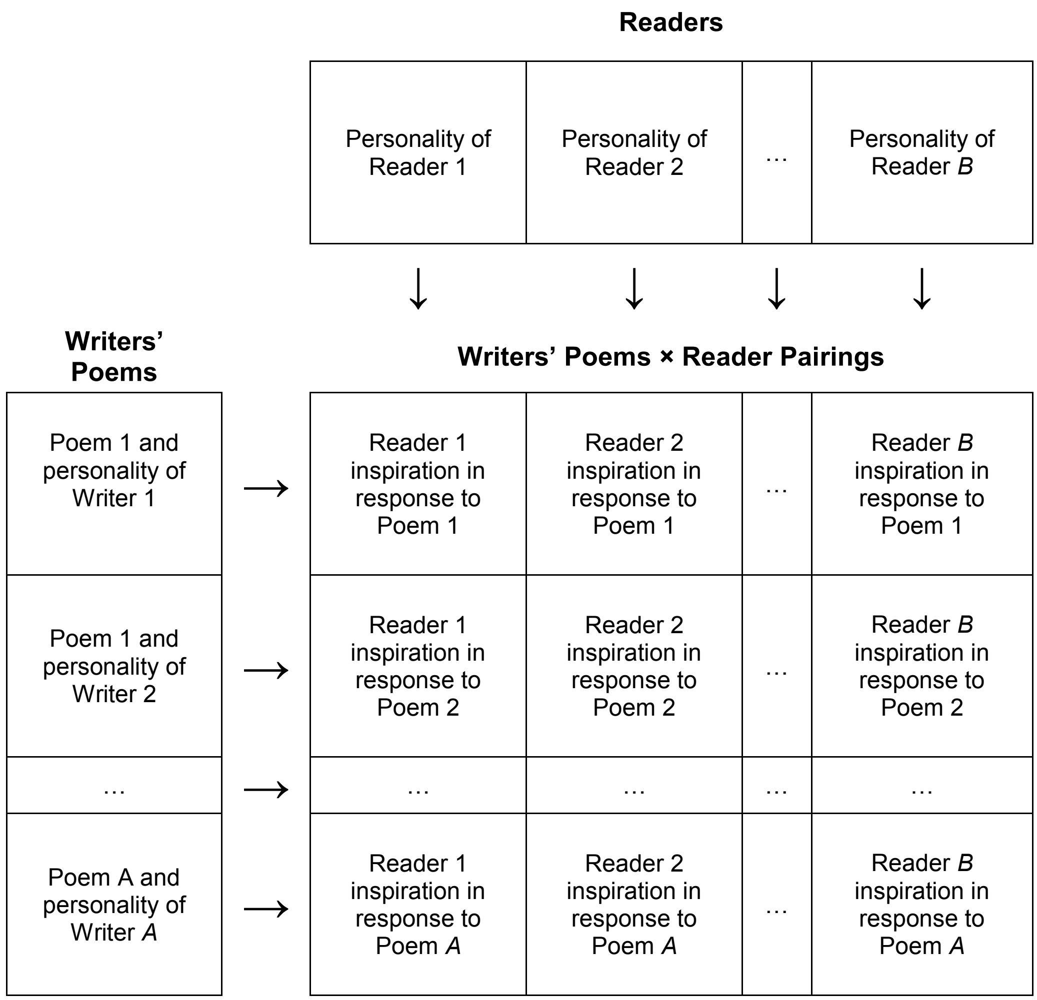

Figure 2. Illustration of writer × reader cross-classified data structure.

Hypotheses

Having discussed relevant theory and empirical work, as well as considering analytical challenges regarding the current study, we formally state our hypotheses in the following section.

Profile Similarity

Our main goal in the current study is to determine whether personality similarity between writers and readers leads to greater inspiration in the reader. In the following, we present two hypotheses pertaining to profile similarity and reader inspiration.

First, we hypothesized that distinctive profile similarity would predict greater reader inspiration. That is, reader inspiration was expected to be greater when writers and readers differ from the average person in a similar way. We also included writer normativity and reader normativity as predictors of reader inspiration. We hypothesized that both writer normativity and reader normativity would predict greater inspiration in the reader. Reader inspiration was expected to be greater when a particular writer is similar to the average reader (i.e., writer normativity). Also, we expected reader inspiration to be greater when a particular reader is similar to the average writer (i.e., reader normativity). We expected these three effects on reader inspiration to be positive.

In addition to our hypotheses about distinctive similarity, writer normativity, and reader normativity, we also conceptualized writer normativity as a moderator variable. Our rationale stemmed from the notion that writer normativity was a particularly salient variable in relation to distinctive similarity, such that a writer’s ability to appeal to a broad reader base may affect the extent to which distinctive similarity impacts reader inspiration. Put another way, given that distinctive similarity captures the extent to which writers and readers differ from the normative profile in similar ways, then a particularly unique writer-reader pairing may be more important for evoking inspiration in the reader when a writer is not able to appeal to the masses (i.e., low writer normativity). Thus, formally stated, we hypothesized that greater writer normativity would attenuate the effect of distinctive profile similarity on reader inspiration.

Single-Trait Similarity

We have one primary hypothesis pertaining to single-trait similarity and reader inspiration. We hypothesized that, for all Big Five traits, single-trait similarity between writers and readers would predict greater reader inspiration. That is, reader inspiration was expected to be greater when writers and readers are similar on a particular trait (e.g., agreeableness). We expected the interaction effect in the polynomial models to be positive and significant for all Big Five traits. Having noted above, however, we theorized that some traits (openness to experience and extraversion) are relevant to inspiration for reasons having nothing to do with writer-reader similarity, and therefore we did not necessarily expect effects to be comparable across traits. Nevertheless, we expected that similarity would be conducive to reader inspiration for all Big Five traits.

Method

We present methods concerning both the writer and reader data collections. Findings from both data sets have been published previously (Writers: study 3 of Thrash et al., 2010; Readers: Thrash et al., 2016). Most writer and reader trait variables were not used previously, however, and no analyses of writer-reader similarity have been reported.

Participants

Writers. The writer sample included 195 undergraduates (50.7% female) who were enrolled in an introductory psychology course. Seven participants were dropped because they reported knowing about the writing topic beforehand. One additional participant started the study but quit before the writing process questionnaire because his or her English was too poor to understand it. Participants received credit towards a research participation requirement upon completion of the study. Ethnicity was distributed as follows: African American, 9.2%; Asian, 4.6%; Caucasian, 80.0%; Hispanic, 2.6%; Native American, .5%; Other, 3.1%.

Readers. The reader sample included 220 undergraduates (70.0% female) who were enrolled in a course on personality and poetry. Seven participants failed to complete personality questionnaires or any poem questionnaires and were dropped prior to analyses. Participants received credit towards a research participation requirement upon completion of the study. As an additional incentive, participants were offered feedback about their scores. Ethnicity was distributed as follows: African American, 7.7%; Asian, 10.0%; Caucasian, 69.1%; Hispanic, 6.4%; Native American, .5%; Other, 6.4%. Both writer and reader samples came from a competitive university with five years between data collections.

Procedure

Writers. Participants attended individual lab sessions and first completed a demographic and personality questionnaire. Participants were then given 30 minutes to write a poem about the human condition using a word processor.

They were granted more time upon request. Finally, participants completed a questionnaire regarding inspiration during particular stages of the writing process.

Readers. Participants attended a preliminary orientation and completed personality questionnaires towards the start of the semester. Throughout the semester, participants read poems at times of their choosing in private locations. For each poem, participants read the poem and answered questions regarding their reactions to the poem (e.g., inspiration). Poems were presented in a random order for each reader.

The poem questionnaire data initially contained 41,397 cases. The data were then cleaned by removing cases that met any of the following criteria: (a) the participant provided no identifying information; (b) the data came from someone who did not provide consent or complete the personality questionnaires; (c) the participant gave an affirmative answer to a question asking whether he or she would want to redo a poem questionnaire at a later time due to disruption or other factors that could have invalidated the data; (d) there were duplications in submissions; (e) time stamps showed that the participant spent less than 2 minutes on the poem questionnaire (2 minutes was the lowest point of a bimodal distribution); (f) the data came from a poem that was erroneously included (this poem came from the writer whose English was too poor to complete the writing process questionnaire). The cleaned file contained 36,020 poem questionnaires, and the number of poem questionnaires per reader ranged from 1 to 195 (median of 193).

Measures

In the following, we present study measures. All descriptive statistics may be found in Table 1.

Writer and Reader traits. *Big Five traits* were measured in both writers and readers using Costa and McCrae's (1992b) 60-item NEO Five Factor Inventory. Agreeableness, Conscientiousness, Extraversion, Neuroticism, and Openness to Experience were each assessed with 12-item sub-scales from the NEO Five-Factor Inventory. Response options ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Composite trait scores were formed by averaging the 12 items corresponding to each trait.

Distinctive profile similarity was computed as follows. First, we subtracted the group average profile from individuals' observed profiles. Second, we reflected the observed distinctive scores and appended the reflected distinctive scores to each profile (Cohen, 1969). Third, we correlated each writer's distinctive profile with each reader's distinctive profile (Furr, 2008). Finally, we used Fisher's z-transformation to normalize the distribution of distinctive profile similarity correlations.

Writer normativity was computed by correlating each writer profile with the average (i.e., normative) reader profile (Furr, 2008). The average reader profile was constant across all readers. Writer profiles and the average reader profile consisted of both observed and reflected scores. Fisher's z-transformation normalized the distribution of writer normativity scores.

Reader normativity was computed by correlating each reader profile with the average (i.e., normative) writer profile (Furr, 2008). The average writer profile was constant across all writers. Reader profiles and the average writer profile consisted of both observed and reflected scores. Fisher's z-transformation normalized the distribution of writer normativity scores.

Reader response. *Inspiration* was measured using the four-item state version of the Inspiration Scale (Thrash & Elliot, 2003). One item from the original scale ("Something I encountered or experienced inspired me") was adapted for the reader study ("Something about the poem inspired me"; Thrash et al., 2016). Response options ranged from 1 (*not at all*) to 7 (*deeply or strongly*). An inspiration composite was formed by summing the four items.

Variable Transformation

We examined variable distributions with Q-Q plots and found strong positive skew in reader inspiration. To reduce skew, reader inspiration was log transformed. This non-linear transformation effectively pulled large values closer to small values.

Table 1.
Descriptive Statistics.

Variable	*M*	*SD*	Range	Cronbach's α
Writer Traits				
Agreeableness	3.69	0.52	2.17-4.75	.77
Conscientiousness	3.34	0.65	1.58-4.83	.87
Extraversion	3.66	0.56	2.00-5.00	.83
Neuroticism	2.65	0.72	1.00-4.67	.88
Openness to Experience	3.54	0.55	1.92-4.58	.78
Reader Traits				
Agreeableness	3.67	0.59	1.83-4.75	.82
Conscientiousness	3.76	0.59	1.92-4.92	.87
Extraversion	3.50	0.59	1.75-4.75	.84
Neuroticism	2.80	0.66	1.00-4.42	.84
Openness to Experience	3.59	0.56	2.08-4.83	.79
Study Variables				
Distinctive Similarity	0.00	0.48	-0.99-1.00	-
Writer Normativity	0.62	0.30	-0.55-0.99	-
Reader Normativity	0.62	0.32	-0.51-0.99	-
Reader Inspiration	0.37	0.48	0.00-1.40	-

Note. Descriptive statistics for distinctive similarity, writer normativity, and reader normativity are not normalized using Fisher's r-to-z transformation in Table 1. Descriptive statistics for reader inspiration is log-transformed. Writer and reader traits are average scores.

Results

Data Plan

The cross-classified multilevel data structure for the current study can be decomposed into three orthogonal levels of variance: Level 2A, Level 2B, and Level 1 (Muthén & Muthén, 2012)[3]. We refer to these three orthogonal levels as the Writer level, the Reader level, and the Writer × Reader level, respectively. It is important to distinguish between these independent levels of analysis in a cross-classified multilevel model because standardized estimates are computed with respect to the variance at each level.

At the Writer level, any variance explained in the outcome variable (i.e., reader inspiration) attributable to a predictor variable measured at the Writer level (e.g., writer extraversion) is due to differences between writers. The Writer level corresponds to the writers' poems and populates the rows on the left margin of Figure 2. Writer normativity in the profile similarity analyses, as well as writer traits in the single-trait similarity analyses, were modeled at the Writer level of analysis (N = 195).

At the Reader level, any variance explained in the outcome variable (i.e., reader inspiration) attributable to a predictor variable measured at the Reader level (e.g., reader extraversion) is due to differences between readers. The Reader level populates the columns on the top margin of Figure 2. Reader normativity in the profile analyses and reader traits in the single-trait analyses were modeled at the Reader level of analysis (N = 220).

At the Writer × Reader level, any variance explained in the outcome variable (i.e., reader inspiration) attributable to a variable measured at the Writer × Reader level (i.e., distinctive profile similarity) is a term that includes writer × reader interaction variance and within-cell variance. Writer × reader interaction variance is variance due to a unique pairing between a writer and a reader, or a two-way interaction between writers and readers. Within-cell variance is variance within each Writer × Reader cell. In the current design, involving only a single observation per cell (e.g., reader 1's response to poem 1), within-cell variance cannot be distinguished from interaction variance (i.e., writer × reader variance). Distinguishing interaction and within-cell variance would have required assessing each reader's reaction to each poem multiple times. Due to practical limitations, such a design was not feasible. Thus, we only have an average effect at the Writer × Reader level. The Writer × Reader level populates the cells of the data matrix in Figure 2. Distinctive profile similarity and reader inspiration were modeled at the Writer × Reader level of analysis (N = 36,020).

Analyses were conducted in Mplus 7.4 (Muthén & Muthén, 2012) using Bayesian estimation (Muthén, 2010). Bayesian estimation was used due to the computationally-complex nature of cross-classified multilevel models. It is too difficult to estimate parameters in cross-classified models using traditional estimation methods (e.g., maximum likelihood) because of the high-dimensionality of the data. We specified diffuse priors as opposed to informative priors because there has been little previous research that informed the expected effect sizes in the current study. Bayesian estimation included use of the Markov Chain Monte Carlo (MCMC) algorithm based on the Gibbs sampler to form the posterior distribution for each variable. Two MCMC chains were used, while the second half of each chain was retained. Model convergence was assessed using the Gelman-Rubin potential scale reduction criterion (Gelman & Rubin, 1992; Muthén & Muthén, 2012). We repeated all analyses setting the minimum number of iterations at four times the number of iterations from the initial analysis. This strategy minimizes the risk of premature model convergence (Muthén & Asparouhov, 2012). All reported point estimates are medians of the posterior distributions. Additionally, Bayesian 95% credible intervals (CIs) provide bounds for statistical significance of effects, and *p*-values are one-tailed and indicate the proportion of the posterior distribution that is below or above zero for positive or negative estimates, respectively.

Variance Decomposition of Reader Inspiration

A cross-classified variant of intraclass correlations (ICCs) indicate the proportions of total variance found at any given level of analysis (Raudenbush & Bryk, 2002). In our model, variance occurs at the Writer level, Reader level, and Writer × Reader level. The percentages of variance for reader inspiration were as follows: Writer level, 5.7%; Reader level, 42.8%, and Writer × Reader level, 51.5%. 5.7% of the total variance occurring at the Writer level indicates a weak tendency for some poems to be more inspiring than other poems. 42.8% of the total variance occurring at the Reader level indicates a strong tendency for some readers to be more inspired than other readers. Finally, 51.5% of the total variance occurring at the Writer × Reader level indicates an even stronger tendency for inspiration to be present in particular writer-reader pairings. A strong tendency for inspiration to be present in certain writer-reader pairings is consistent with our hypothesis that matching writers and readers on personality traits predicts greater reader inspiration.

Profile Similarity

We used a random-intercept model to formally test the effects of distinctive personality similarity, writer normativity, and reader normativity on reader inspiration[4]. Reader inspiration was regressed on distinctive similarity at the cell level, writer normativity at the Writer level, and reader normativity at the Reader level. The intercept was allowed to vary at all levels.

We also used a random-slope-and-intercept model to test whether writer normativity moderated the effect of distinctive similarity on reader inspiration. Distinctive similarity, writer normativity, and reader normativity were measured at the Writer × Reader level, the Writer level, and the Reader level, respectively. Reader inspiration was regressed on distinctive personality similarity, with the intercept free to vary at all levels and the slope free to vary across writers. The random effect of distinctive personality similarity was regressed on writer normativity, such that writer normativity moderated the effect of distinctive personality similarity on reader inspiration.

Distinctive profile similarity. Fixed effects are in standardized form and shown in Table 2. The fixed effect of distinctive personality similarity on reader inspiration was positive as hypothesized, with the 95% CI excluding zero [.027, .048]. The point estimate was .039 ($p < .001$). This indicates that readers are more inspired when writers and readers differ from the average profile in similar ways.

The fixed effect of writer normativity on reader inspiration was also positive as hypothesized [.037, .357]. The point estimate was .194 ($p < .05$). This indicates that readers are more inspired when writers are similar to the average reader. Indeed, writers who appeal to a broad reader base are more likely to inspire readers. The fixed effect of reader normativity on reader inspiration was not significant [-.086, .051]. The point estimate was -.018 ($p = .280$).

Writer normativity as a moderator. Random effects are unstandardized and shown in Table 2. The random effect of distinctive similarity on reader inspiration was regressed on writer normativity. This provided a test of moderation. As hypothesized, greater writer normativity attenuated the effect of distinctive similarity on reader inspiration, such that zero was not included in the 95% CI [-.024, .000][5]. The point estimate was -.015 ($p < .05$). This provides evidence that a unique writer-reader pairing is more important for reader inspiration when the writer is dissimilar to the average reader.

In summary, distinctive similarity and writer normativity predicted greater reader inspiration. In addition, greater writer normativity attenuated the effect of distinctive similarity on reader inspiration. These results provide evidence in favor of our profile similarity hypotheses. We turn next to single-trait similarity predicting reader inspiration.

Table 2
Random-Intercept and Random-Slope-and-Intercept Models Predicting Reader Inspiration

Similarity Variable	Fixed Effects (β)	Random Effects (β)
Model 1 – Random-intercept (standardized effects)		
Distinctive similarity	**.039 [.027, .048]**	**-**
Writer normativity	**.194 [.037, .357]**	**-**
Reader normativity	-.018 [-.086, .051]	-
Model 2 – Random-slope-and-intercept (unstandardized effects)		
Distinctive similarity	**.033 [.018, .048]**	**-**
Writer normativity	**.039 [.003, .070]**	**-**
Writer normativity x Distinctive similarity	-	**-.015 [-.024, .000]**

Note. Significant results are bolded. Point estimates are one-tailed and credible intervals are 95%.

Single-Trait Similarity

Due to the two-dimensional nesting structure of our dataset, each polynomial model was tested within a cross-classified multilevel framework[6]. The single-trait similarity hypothesis was tested using a random-intercept model for each Big Five trait. The intercept was allowed to vary at all levels. All polynomial results are standardized and can be found in Table 3.

Agreeableness. The fixed effects of writer agreeableness, reader agreeableness, and both quadratic terms were not significantly different than zero. The interaction term between writer agreeableness and reader agreeableness was positive and significant [0.013, 0.055]. The point estimate was .034 ($p < .001$). This result provides evidence that writers and readers who were both high or low on agreeableness yielded greater inspiration in readers. The full agreeableness polynomial model is graphed in Figure 3. We repeated these analyses by excluding the quadratic terms and retaining only the main effects and interaction term in the model. All fixed effects in the reduced model were significant and positive.

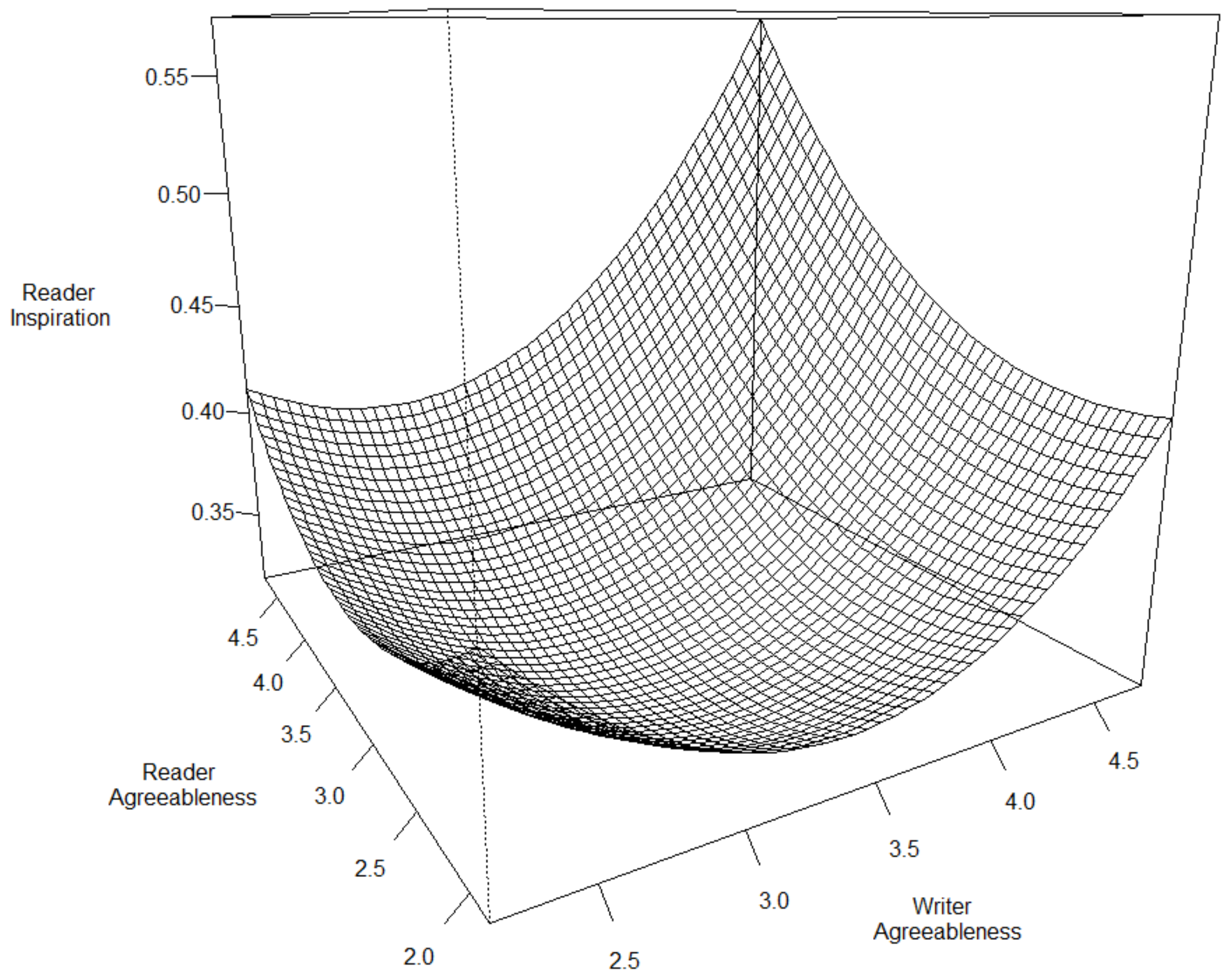

Figure 3. Agreeableness. Graphical representation of the full polynomial model (i.e., including quadratic terms) for writer-reader similarity on agreeableness and the effect on reader inspiration.

Conscientiousness. The fixed effects of reader conscientiousness, as well as the writer and reader quadratic terms were not significantly different than zero. The fixed effect of writer conscientiousness was positive, such that zero was not included in the 95% CI [.009, .131]. The point estimate was .072 ($p < .05$). The interaction effect between writer conscientiousness and reader conscientiousness was also positive [.005, .040]. The point estimate was .023 ($p < .01$). This suggests that writers and readers who were both high or low on conscientiousness yielded greater inspiration in readers. The full conscientiousness polynomial model is graphed in Figure 4. We repeated the analyses without the quadratic terms included in the model and found similar results.

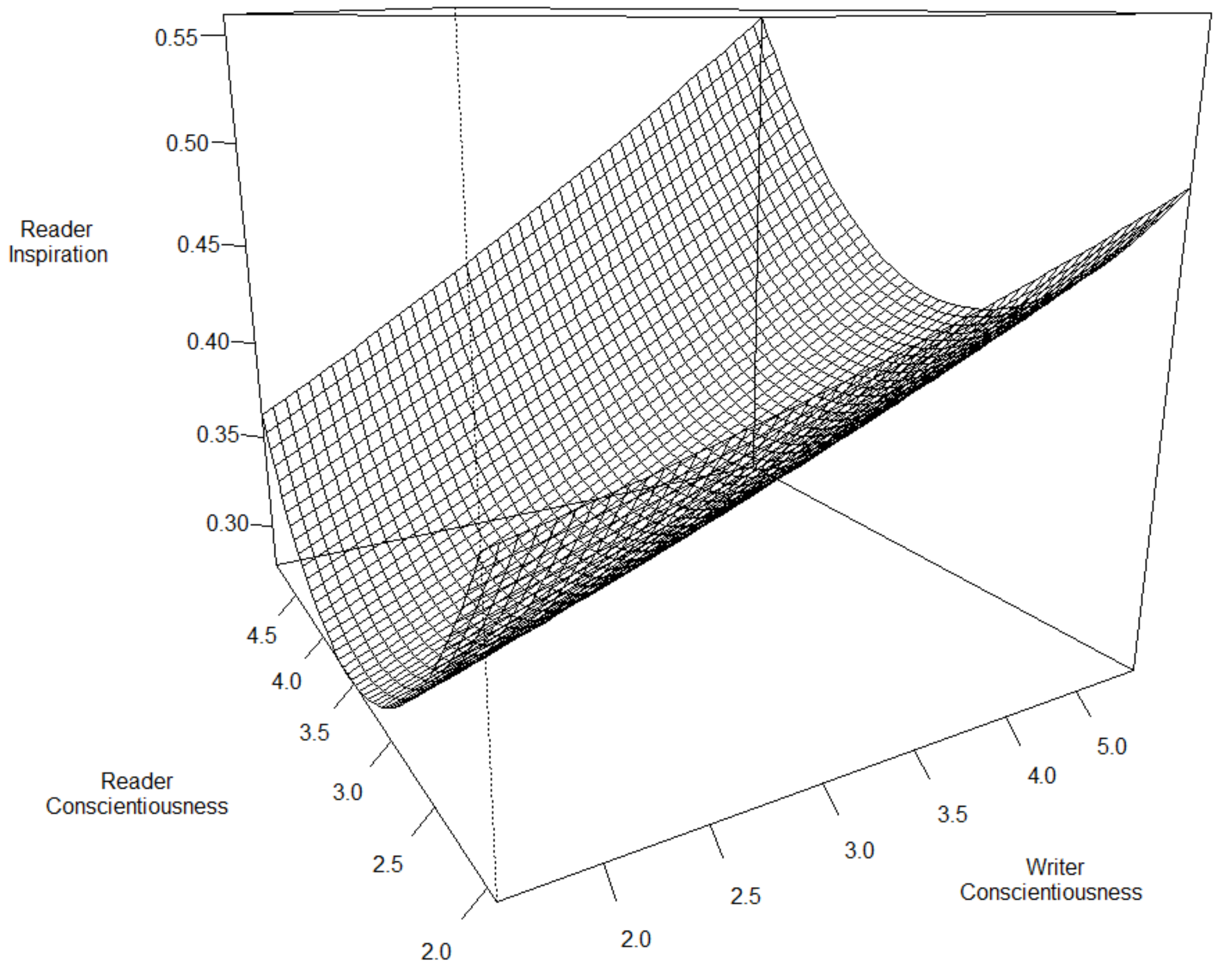

Figure 4. Conscientiousness. Graphical representation of the full polynomial model (i.e., including quadratic terms) for writer-reader similarity on conscientiousness and the effect on reader inspiration.

Extraversion. The fixed effects of writer extraversion, reader extraversion, and the corresponding quadratic terms were not significantly different than zero. The interaction effect between writer extraversion and reader extraversion was positive [.016, .052]. The point estimate was .034 ($p < .001$). This suggests that writers and reader who were both high or low on extraversion yielded greater reader inspiration. See Figure 5 for the full extraversion polynomial model graphed. Analyses were repeated without the quadratic terms. The main fixed effect of writer extraversion and the interaction term in the reduced model were both significantly positive.

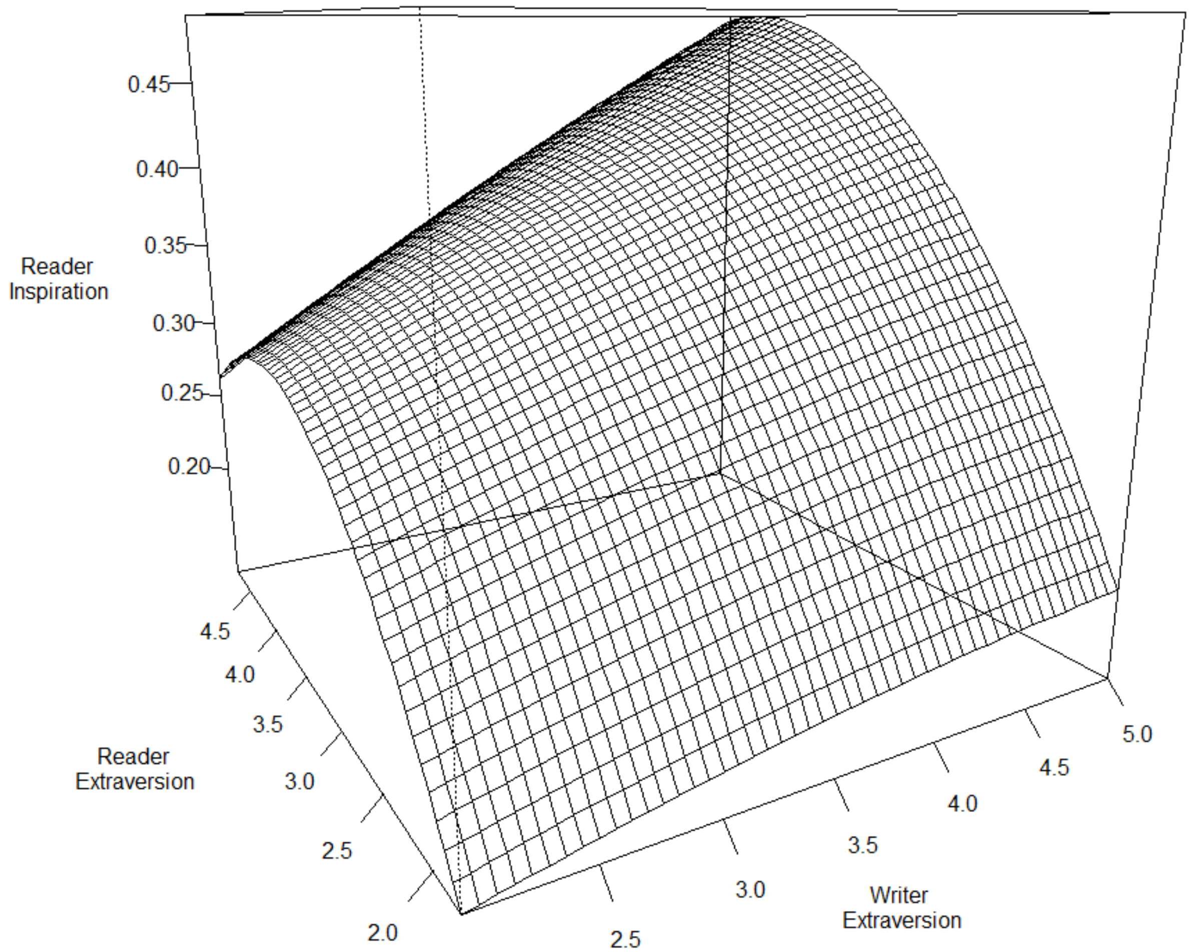

Figure 5. Extraversion. Graphical representation of the full polynomial model (i.e., including quadratic terms) for writer-reader similarity on extraversion and the effect on reader inspiration.

Neuroticism. The fixed effects of writer neuroticism, reader neuroticism, and both the writer and reader quadratic terms were not significantly different than zero. The interaction effect between writer neuroticism and reader neuroticism was positive [.010, .033], suggesting that writers and readers who were both high or low in neuroticism yielded greater inspiration in readers. The point estimate was .022 (p < .001). The full polynomial model is graphed in Figure 6. We also repeated the analyses by excluding the quadratic terms. In the reduced model, writer neuroticism retained a negative coefficient, while reader neuroticism predicted greater reader inspiration. The interaction effect remained significant and positive.

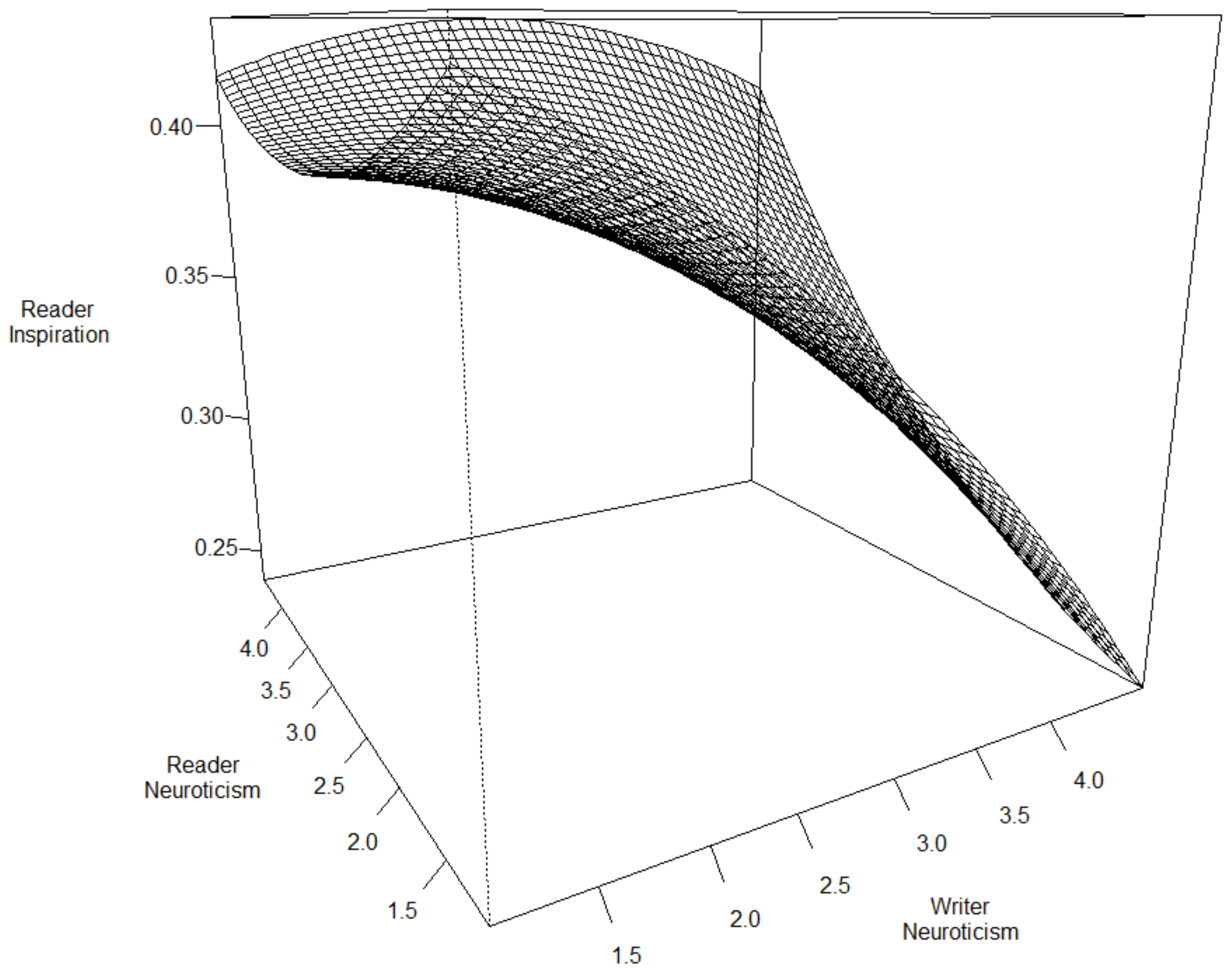

Figure 6. Neuroticism. Graphical representation of the full polynomial model (i.e., including quadratic terms) for writer-reader similarity on neuroticism and the effect on reader inspiration.

Openness to Experience. The fixed effects of writer openness, reader openness, and both the writer and reader quadratic terms were not significantly different than zero. Consistent with all other Big Five traits, the interaction term between writer openness and reader openness was positive [.037, .072]. The point estimate was .054 (p < .001). This indicates that writers and readers who were both high or low in openness yielded greater reader inspiration. The full polynomial model is graphed in Figure 7. We repeated these analyses by excluding the quadratic terms. We found that the effect of writer openness on reader inspiration was significant and negative, while the interaction term was significant and positive.

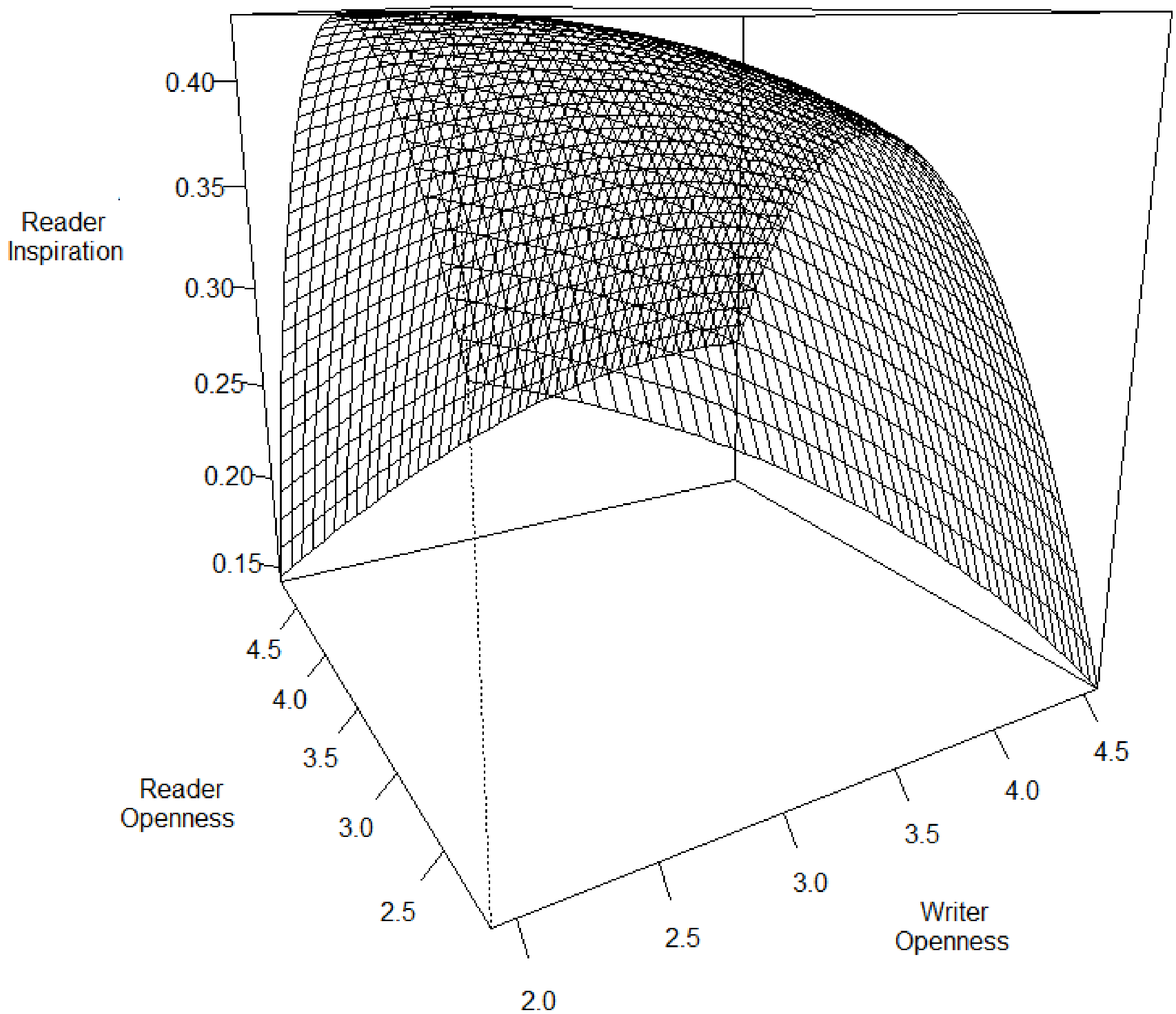

Figure 7. Openness to Experience. Graphical representation of the full polynomial model (i.e., including quadratic terms) for writer-reader similarity on openness to experience and the effect on reader inspiration.

All polynomial models failed to meet Edward’s (2002) requirements for model support because every quadratic term was non-significant. Due to this result, we did not test for congruence effects using response surface methodology. We did, however, find significant and positive interaction effects for all Big Five traits. We discuss these polynomial results, as well as the profile similarity results, in light of our hypotheses.

Table 3.

Random-Intercept Polynomial Models Predicting Reader Inspiration.

Trait Model	Writer trait (β)	Reader trait (β)	Writer x Writer trait (β)	Reader x Reader trait (β)	Writer × Reader trait (β)
Agreeableness	-.022 [-.128, .077]	.010 [-.141, -.192]	.094 [-.001, .191]	.026 [-.149, .206]	**.034** **[.013, .055]**
Conscientiousness	**.072** **[.009, .131]**	-.129 [-.318, .054]	.001 [-.050, .059]	.198 [-.007, .407]	**.023** **[.005, .040]**
Extraversion	.082 [-.008, .171]	.053 [-.107, .230]	-.015 [-.108, .073]	-.030 [-.187, .169]	**.034** **[.016, .052]**
Neuroticism	-.047 [-.096, .003]	.082 [-.035, .204]	-.015 [-.067, .038]	.003 [-.112, .135]	**.022** **[.010, .033]**
Openness to Experience	-.041 [-.111, .039]	.043 [-.145, .226]	-.029 [-.106, .044]	-.115 [-.301, .100]	**.054** **[.037, .072]**

Note. Significant results are bolded. Point estimates are one-tailed and credible intervals are 95%. Effects are standardized.

General Discussion

There has been considerable debate within literary criticism about the most important features of the literary process. For instance, theorists in the school of New Criticism do not focus on historical reference or philosophical analysis to argue about the writer’s intent or how readers interpret the text (Ransom, 1963). They instead focus solely on the structure and form of the text to understand its meaning. Conversely, reader-response theorists focus on how readers interpret and make meaning from text. They argue that the convergence of text and reader explains why meaning in text is always in a state of flux (Iser, 1974). We argue, however, that literary theorists have made little progress in parsing apart the good theories from the bad. In the current study, we used the scientific method to determine whether a particular literary theory was empirically supported. We hypothesized that personality similarity between writers and readers would lead to greater inspiration in the reader.

The results largely supported our hypothesis. Distinctive personality similarity – the extent to which a writer and reader differed from the average profile in a similar way – predicted greater inspiration in the reader. Distinctive similarity is a valid measure of personality similarity because it removes normativity (i.e., socially desirable responses) from writers' and readers' profile scores. Thus, in finding a significant positive effect, we gained support for our first hypothesis. This is noteworthy because it shows that the scientific method can help address questions that are difficult to evaluate using the methods of literary theory.

In addition to distinctive similarity, we found that writer normativity – the extent to which a writer is similar to the average reader – also predicted greater reader inspiration. This effect was considerably larger than the effect of distinctive similarity. We also tested writer normativity as a moderator of the effect of distinctive similarity on reader inspiration and found a significant and negative effect. This result suggests that, if a writer was dissimilar to the average reader, it was more important that he or she be distinctly similar (or unique in a similar way) to a given reader in order to elicit inspiration in that reader. This finding also indicates that writer normativity can also be conceptualized as a moderator of the effect of distinctive similarity on reader inspiration. In contrast to writer normativity, reader normativity did not predict reader inspiration as we hypothesized. It is possible that readers who were more similar to the average writer are unlikely to be inspired at all because the average writer may not have much to say. More research needs to be done to elucidate this null finding.

In addition to profile similarity, we hypothesized that writer-reader similarity for all Big Five traits would predict greater reader inspiration. Our hypothesis was not supported. The quadratic terms in all five polynomial models were not significant, and thus, we could not test for congruence using response surface methodology. The interaction effects in all five polynomial models, however, were significant and positive. This supports a certain kind of single-trait similarity hypothesis: writers and readers who were both high or both low on a particular trait, but not both average, lead to greater inspiration in the reader.

To understand why we did not find significant quadratic effects, it is possible that writers and readers who are both average on a trait fail to elicit inspiration in the reader at all. Writers and readers who are similarly extreme on a trait may be more likely to elicit a rarely occurring experience in the reader such as inspiration. Also, we did not find support suggesting that similarity on extraversion and openness to experience was less important for predicting reader inspiration. In fact, the strongest effect occurred for openness to experience. This suggests that writer-reader similarity on openness to experience is particularly important for eliciting greater inspiration in the reader. This finding may be due to the fact that individuals high and low in openness tend to have quite different interests and values (e.g., liberal vs. conservative political preferences, respectively), and that these differences may have a substantial impact on reader inspiration. Finally, it is possible that complementary dispositions between writers and readers may affect reader inspiration in other domains. Although we found evidence for the effect of writer-reader similarity on reader inspiration in the context of poetry, it is conceivable that other contexts of writing may show writer-reader complementary effects. For example, if the writing pertains to self-help, highly conscientious readers may be inspired by low conscientious writers, while low conscientious readers may be inspired by highly conscientious writers. This might be the case because readers of self-help will likely be high on neuroticism, and in combination with another trait (e.g., reader conscientiousness), may find inspiration in the opposite manifestation of that trait in the writer (e.g., writer conscientiousness). Researchers should examine other domains of writing to see whether similar or complementary dispositions between writers and readers are more conducive for reader inspiration or other positive reader responses.

In summary, the profile similarity results and the single-trait similarity results provide evidence that personality similarity between writers and readers leads to greater inspiration in the reader.

Limitations

We note some limitations in the study. First, the effect sizes were small by conventional standards for most of our results (Cohen, 1988). Small effect sizes may hinder the meaningfulness of our findings, but do not necessarily weaken the validity. On one hand, small effect sizes signify that our main variable of interest (i.e., distinctive personality similarity) explains a small portion of the variance in reader inspiration. This calls into question how meaningful personality similarity is for predicting inspiration in the reader. On the other hand, the complexity of the literary process may preclude most variables from explaining a large amount of the variance in reader inspiration. Many factors likely cause reader inspiration, one of which may be personality similarity between writers and readers. Additionally, we used distal variables in the form of writer and reader personality to predict inspiration. Writers and readers never came into contact with each other, except through writers' poems. Thus, it may be misguided to expect medium to large effect sizes for variables as distal as personality traits.

Of note, writer normativity may be a factor which explains a good portion of variance in reader inspiration. In the current study, writer normativity strongly predicted greater reader inspiration. Writers who are similar to the average reader may be able to appeal to a common sense of meaning in readers. To understand this finding, we call on researchers to further investigate writer normativity in the context of positive reader responses.

A second limitation in the current study is our use of observed variables rather than latent variables. Although Mplus uses a latent variable approach to estimate the cluster means in multilevel modeling, we did not model measurement error in the personality traits and inspiration. We note that our effects would likely be strengthened if we modeled our study variables as latent.

Closing Comments

Despite the limitations, the current findings are valuable because (1) they elucidate the nature of Auden’s “lucky accidents”, and (2) they show that ideas from the humanities can be tested using scientifically validated methods. Although scientists have been late to the party in evaluating rich ideas found in literary theory, we must go beyond the theorizing that occurs in literary criticism to understand what is true in literature. We believe that there needs to be a more reliable feedback mechanism. Gallagher (1997) noted that literary criticism has always been in a state of crisis. This crisis, she argues, is a result of common reactions to various intellectual movements. Literary theorists may be at the whim of these intellectual movements without any solid foundation to rest upon. In the current study, we used the scientific method not because science is immune to reactionary movements or is in a state of static understanding, but rather because it has an alternative feedback mechanism – nature. If we have proper tools for measurement, employ methodologically rigorous study designs, and combine present theory with past empirical evidence in a logically consistent manner, nature may reveal to us what is closer to the truth than what is not. Finally, we argue that it is not the exclusion of the humanities from sciences that progresses knowledge, but rather it is the union between the two that will lead to a greater understanding of literature. Thus, we call on researchers to bridge the gap between literary criticism and science by evaluating literary theories using the scientific method.

Footnotes.

1. To accurately reflect this work as a collaborative project, I used plural pronouns throughout.
2. Example quadratic polynomial model:
   $Y_i = b0 + b1X_i + b2Z_i + b3X_i^2 + b4Z_i^2 + b5X_iZ_i + e_i$; where
   Y_i is reader inspiration in person i;
   X_i is writer extraversion in person i;
   Z_i is reader extraversion in person i;
   $X^2{}_i$ is quadratic term for writer extraversion in person i;
   $Y^2{}_i$ is quadratic term for reader extraversion in person i;
   X_iZ_i is interaction term for writer and reader extraversion in person i;
   e_i is error in predicting reader inspiration in person i;
   b0 is intercept;
   b1, b2, b3, b4, and b5 are coefficients relating IV scores to DV score.
3. The Writer × Reader level may be decomposed into two additional orthogonal levels of variance: a Within-cluster component and a Between-cluster component (Muthén & Asparouhov, 2011). Any variables measured at the Writer × Reader level (i.e., dependent or independent variables) may, in theory, have both a Within-cluster variance component and a Between-cluster variance component. Since the dependent variable of reader inspiration is measured at the Writer × Reader level, any variance explained in this variable may, in theory, occur either at a Within-cluster level or at a Between-cluster level. Independent variables measured at the Writer × Reader level (e.g., distinctive profile similarity) may, in theory, also affect both the Within-cluster level and Between-cluster level of a Writer × Reader level outcome variable. These effects have been referred to as Within effects and Between effects, respectively (Preacher, Zyphur, Zhang, 2010). Moreover, independent variables measured at the two upper levels – Writer level or Reader level – may, in theory, only affect the Between-cluster level of the Writer × Reader level outcome variable. That is, Writer level or Reader level independent variables may only have Between effects on a Writer × Reader level variable. In the current study, we have only one observation per cell; for example, reader 1 inspiration in response to poem 1. This means that there is no Within-cluster variance to estimate in Writer × Reader level variables. Thus, Writer × Reader predictors may only have Between effects on Writer × Reader outcome variables in the current study.
4. We ran another cross-classified multilevel model using overall similarity between writers and readers (i.e., observed scores without removing normativity) as a Writer × Reader level variable. Variance decomposition in Mplus allows for variance to be partitioned at all three levels of analysis; that is, the Writer × Reader level, the Writer level, and the Reader level. Variance at each of these levels corresponds to distinctive similarity, writer normativity, and reader normativity, respectively. Variance at the Writer × Reader level (i.e., distinctive similarity) predicted greater reader

inspiration, .032 ($p < .001$). Variance at the Writer level (i.e., writer normativity) predicted greater reader inspiration, .246 ($p < .001$). Variance at the Reader level (i.e., reader normativity) did not predict reader inspiration, .037 ($p = .290$). Note the similarity of these standardized effect sizes with that of the original results. This method may provide more accurate effect sizes than the reported study results because Mplus uses a latent variable approach to estimating the cluster means in multilevel modeling, while our original approach did not. We did not use this technique, however, because we could not use the variance captured at the Writer level (i.e., writer normativity) as a moderator of variance at the Writer × Reader level (i.e., distinctive similarity) in Mplus.

5. The 95% CI does not include zero. Mplus prints three decimal values, but indicates whether an effect is significant or not with an asterisk in the output. The moderation effect of writer normativity was significant with an asterisk.
6. The cross-classified polynomial models estimated in Mplus retained similar, although not exact effect size magnitudes compared to the polynomial models estimated using traditional multiple regression. The effect sizes were not exact because Mplus partitions variance in Level 2 (i.e., Writer level and Reader level) variables into error variance and latent variance by using the units (i.e., writer × reader cells) nested in clusters (i.e., writers and readers) as indicators of Level 2 variables. Writer level and Reader level variables were latent, and thus yielded slightly different coefficient estimates. As expected, the standard errors in the polynomial models were considerably larger using the cross-classified multilevel model compared to using the multiple regression model. This result was expected because multilevel models typically adjust standard errors up to their properly specified alpha level of .05 when there is systematic non-independence of observations in a sample.

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