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RESEARCH NOTE

REVIEWING FROM A DISTANCE: UNCOVERING ASYMMETRIC MODERATIONS OF SPATIAL AND TEMPORAL DISTANCE BETWEEN SENTIMENT NEGATIVITY AND RATING[1]

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Drawing on construal level theory, prior literature has found a positivity bias in online ratings when consumers evaluate an experience from a psychological distance, whether spatial or temporal. Self-distancing theory posits that psychological distance enables individuals to reflect on psychologically distant negative experiences more genuinely, in a less biased way. This raises the question of whether the positivity bias in ratings due to psychological distance persists for negative experiences. To address this question, we collected data from a large review platform that enables the identification of reviewers' spatial and temporal distance. The negativity of an experience was operationalized via review text sentiment. We introduced spatial and temporal distance as moderators between sentiment negativity and ratings and found a negative moderation by spatial distance and a positive moderation by temporal distance. Our findings indicate that the relationship between sentiment negativity and rating grows stronger under spatial distance and gets weaker under temporal distance. Text mining confirmed self-distancing as the driver behind the spatial moderation and construal levels as the driver behind the temporal moderation. We attribute the asymmetric moderations to differences in the tangibility of spatial distance (more tangible) and temporal distance (less tangible). These results improve our understanding of reviewing behavior and can help platforms de-bias ratings.

Keywords: Online word-of-mouth, spatial distance, temporal distance, construal level, self-distancing, sentiment, rating

Introduction

Based on the 20-year tradition in psychology and marketing research (Maglio, 2020), psychological distance is defined as an "egocentric [perception of] the different ways in which an object might be removed [from] the reference point of self in [the] here and now" (Trope & Liberman, 2010, p. 440). It can be induced by spatial, temporal, social, or hypothetical distance between an object and an individual's "here and now." Scholars have investigated the role of psychological distance in determining outcomes such as decision-making, persuasion, negotiation, creativity, and consumer evaluation (Huang et al., 2016; Stamolampros & Korfiatis, 2018; Trope et al., 2007).

[1] Gal Oestreicher-Singer was the accepting senior editor for this paper. Min-Seok Pang served as the associate editor.

The growing importance of digitized consumption evaluations in the form of online reviews has contributed to a growing interest in this concept by information systems (IS) and marketing scholars. For example, drawing on construal level theory (CLT), prior research (Huang et al., 2016) has found positive effects of psychological distance on online ratings for restaurants. This work has primarily focused on spatial distance (how far a reviewer traveled to the restaurant) and temporal distance (how much time has elapsed between the consumption experience and the review writing). According to CLT, spatial or temporal distance to a restaurant experience causes reviewers to form abstract memories. This makes them focus more on positive aspects, resulting in a positivity bias in ratings (Huang et al., 2016).

Complementary to this, studies have proposed two further theoretical angles on psychological distance. First, self-distancing theory (SDT) introduces a distinction between positive and negative experiences and postulates that psychological distance fosters a genuine evaluation of psychologically distant negative experiences (Kross & Ayduk, 2017). Conceptually, this suggests that for such experiences, the positivity bias in ratings may be less prevalent. Second, spatial and temporal distance differ in their tangibility (Zhang & Wang, 2009). This suggests that a separate analysis of these two distance dimensions is needed to capture whether tangibility leads to asymmetric outcomes in consumer evaluations.

In this study, we incorporated both angles into the analysis of online reviewing from a psychological distance. Specifically, we analyzed situations of consumers having negative experiences and evaluating them online—in spatial or temporal distance—with numerical ratings and accompanying review text. To capture negative experiences, we used the sentiment negativity of the review text. Our goal was to shed light on whether the relationship between sentiment negativity and numerical ratings is moderated by psychological distance, and if so, whether this moderation is asymmetric for spatial and temporal distance. Thus, our research question is as follows: *How does spatial and temporal distance moderate the relationship between the negativity of an experience and online ratings?*

To answer this question, we analyzed a TripAdvisor data set of 1,206,156 consumer reviews with variation in psychological distance along spatial and temporal dimensions. Our study yielded two main results. First, we found a negative moderation by spatial distance, such that the negative relationship between sentiment negativity and ratings becomes stronger under spatial distance. Second, we found a positive moderation by temporal distance, meaning that the relationship between sentiment negativity and ratings gets weaker under temporal distance.

Our work makes three important contributions. First, we add to the literature on psychological distance and online ratings by analyzing the case of negative experiences. Prior work rooted in CLT has found a positivity bias associated with psychological distance in online ratings (Huang et al., 2016). We found that spatial distance negatively moderates the relationship between sentiment negativity and ratings, suggesting that the positivity bias in ratings via spatial distance is less pronounced for negative experiences. We explain this by theorizing based on SDT. Second, we contribute to the literature on differences between spatial and temporal distance. Earlier work has found that spatial distance is more tangible, less abstract, and creates psychological distance more effectively than temporal distance (e.g., Lackoff, 1990; Zhang & Wang, 2009). We illustrate that the tangibility of psychological distance serves as a differentiator of whether psychological distance fosters self-distancing or higher construal levels. Whereas the spatial moderation is consistent with self-distancing behavior, the temporal moderation reflects the patterns of CLT. Third, our results contribute to the nascent stream of research on the relationship between the sentiment of a review text and its rating. Recent literature has highlighted inherent discrepancies between these two constructs (Kim, 2021; Schoenmueller et al., 2020). Our work contributes to explaining these discrepancies by showing that psychological distance shapes the relationship between these two constructs. For positive experiences, spatial and temporal distance accentuates the discrepancy between ratings and sentiment. For very negative experiences, spatial and temporal distance does not accentuate this discrepancy.

Our results are also valuable for practitioners. The former chief operating officer of Yelp called for initiatives to de-bias reviewing behavior on online rating platforms (Donaker et al., 2019). A crucial step toward de-biasing is identifying review biases in the first place, which is what this study contributes. Not identifying and addressing review biases can have several detrimental consequences. For review platforms (e.g., TripAdvisor or Yelp), failing to de-bias ratings means they might lose consumer trust (Bolton et al., 2013). For consumers, relying on biased ratings can alter purchase decision-making and reduce consumer surplus (Hu et al., 2017). For businesses that are ranked on review platforms based on their ratings, rating biases may alter their rankings, which can affect business performance (Kokkodis & Lappas, 2020).

Theoretical Backgrounds and Hypotheses Development

Psychological Distance, Online Ratings, and Sentiment

Three streams of literature are most pertinent to our study. The first stream of literature is concerned with the effect of psychological distance on online ratings (Huang et al., 2016; Stamolampros & Korfiatis, 2018). Using a data set from TripAdvisor, Huang et al. (2016) found that spatial and temporal distance is associated with a positivity bias in online ratings for restaurants, which is boosted when both temporal distance and spatial distance are present simultaneously. Stamolampros and Korfiatis (2018) confirmed this positivity bias using online rating data for hotels from TripAdvisor and booking.com. Both studies support the view that the positive effect on ratings operates via CLT. In light of potential effects due to self-distancing, it has yet to be determined whether spatial and temporal distance also induces a positivity bias in the ratings of negative experiences in particular.

The second stream of literature deals with differences between spatial and temporal distance. Even though the predominant view in the literature is that spatial distance and temporal distance are uniform “currencies” of psychological distance (Maglio et al., 2013), experimental evidence suggests an inherent difference between the two (Zhang & Wang, 2009). Although priming participants with spatial distance can lead to perceived temporal distance, temporal distance cannot induce spatial distance because spatial distance is a directly meaningful and tangible concept (Lakoff, 1990), whereas temporal distance, or the concept of time, is more abstract and less tangible but can be represented metaphorically by spatial distance. (For example, “the deadline is *far* away.”) Consequently, spatial distance, because it is more tangible, affects perceptions of less tangible concepts such as time. Kim et al. (2012) added to this notion by demonstrating that people often use spatial distance to describe temporal distance but not vice versa. However, there is a gap in the literature concerning the consequences of the differences between spatial and temporal distance dimensions for consumer evaluation.

The third stream of literature concerns the relationship between the sentiment of review texts and the associated numerical rating. Sentiment analysis refers to the “computational study of people’s opinion, attitudes, and emotions towards an entity” based on text (Medhat et al., 2014, p. 1093). Online ratings compress a consumer’s experience to a value on a numerical scale, most commonly from 1 to 5 (Gutt et al., 2019b). With the rise of e-commerce platforms, research interest in sentiment and ratings has proliferated (Pang & Lee, 2008). IS and marketing studies in the early 2000s focused primarily on the role of ratings on economic outcomes (e.g., sales) and on what drives these ratings. (See Babić Rosario et al. (2016) for a meta-analysis.) In the following years, arguably due to advances in natural language processing and machine learning capabilities, sentiment analyses came to the fore (Pang & Lee, 2008). Both sentiment and ratings have since been investigated extensively, and recent literature (Kim, 2021; Schoenmueller et al., 2020) has emerged that examines the discrepancies among these constructs. Conceptually, the most striking disparity is the capability of written text to capture the richness of an experience better than numerical values with predefined manifestations (Brutus, 2010; Daft & Lengel, 1986). Schoenmueller et al. (2020) found that the sentiment of review texts exhibits less skewness in its distribution than numerical ratings and called for future research on the relationship between these two variables. Kim (2021, p. 1) noted that “sentiment scores [from review texts] might be less prone to extremity bias compared to online review ratings. Sentiment scores tended to fit a normal distribution while online review ratings were skewed to extreme values.” These observations are consistent with earlier ones regarding decision-making in performance appraisals. Written comments are much richer and may be at odds with numerical performance appraisals, even when a discrepancy is not deliberately intended (Brutus, 2010). Hence, while there is an apparent discrepancy between sentiment and ratings, research on the factors that moderate this discrepancy is scant.

Self-Distancing and Construal Level in Online Reviewing Behavior

In many instances, consumers reviewed experiences well after they took place and in locations different from where the experiences occurred. Hence, psychological distance is ubiquitous, for instance, when reviewing restaurant experiences online. This has consequences for a consumer’s reviewing behavior. In the following, we draw on SDT (H1) and CLT (H2) to delineate our hypotheses.

According to SDT, individuals can take two distinct perspectives when reflecting on an experience (Kross & Ayduk, 2011): *self-immersed* and *self-distanced*. In the self-immersed perspective, individuals relive the experience before their eyes (Kross & Ayduk, 2017). When reviewers review an experience soon after consumption and in the same city, they remain rather self-immersed. In the setting of a self-immersed perspective, past research has demonstrated that individuals tend to frame negative experiences in their favor, referred to as *self-protection* or *protection of the self-view*

(Blaine & Crocker, 1993). Framing one's own performance in a more positive light (Arkin & Maruyama, 1979) and assigning more positive traits to oneself and more negative traits to others (Brown et al., 1988) are examples of this tendency. For online reviewers, this means their ratings tend to be positive due to self-protection. Self-protection is particularly important in online word-of-mouth settings because consumers' digitized ratings are freely and readily accessible to a large audience (Hennig-Thurau et al., 2004).

Individuals adopting a self-distanced perspective "take a step back" (Kross & Ayduk, 2011, p. 187) from the experience when remembering it. They might provide a review of an experience a couple of weeks or months later and a few hundred miles away. In this case, reviewers are rather self-distanced due to psychological distance. Previous work has shown that individuals who are self-distanced when remembering experiences feel less distressed and are better at making meaning of their experiences (Kross & Ayduk, 2011). They also exhibit lower levels of emotional reactivity (Kross et al., 2005; Kross & Ayduk, 2011; Kross & Ayduk, 2017). Hence, since psychological distance helps individuals cope with and overcome negative experiences, there is no need for self-protection.

Consistent with media richness theory (Daft & Lengel, 1986), we argue that self-protection mainly manifests via the numerical rating that reviewers publicly and readily assign to an experience. Ratings are easily interpretable and thus represent a signal to readers in established frames of reference—a 5-point scale. By contrast, review texts have more information richness, are more nuanced, and require more effort for readers to understand (Daft & Lengel, 1986). Thus, describing a negative experience in a review text requires less self-protection because the review is more difficult to process for review readers. This is also substantiated by literature that considers review sentiment from written text a more effective way of measuring consumer experience (Archak et al., 2011) because ratings are more prone to biases (Schoenmueller et al., 2020). Therefore, we use review sentiment to measure the positivity or negativity of a consumption experience.

Based on SDT, we theorize that psychological distance will prevent reviewers from engaging in self-protection or rating negative experiences higher than warranted. Conceptually, this implies that the relationship between sentiment negativity and rating is moderated by psychological distance. This moderation, however, depends on whether psychological distance can effectively enable self-distancing. Past studies have informed us about the difference between spatial and temporal distance. Specifically, Zhang and Wang (2009) found that spatial distance is more tangible than temporal distance. This difference is founded in the theory of metaphorical reasoning (Lakoff, 1990), according to which the human cognitive system is structured around a set of fundamental experiential concepts. Spatial distance is one such fundamental concept. It emerges out of physical experience and is thus tangible (Lakoff, 1990; Zhang & Wang, 2009). By contrast, temporal distance is abstract and cannot be directly physically experienced. Thus, it is less tangible. People often use fundamental (tangible) concepts as metaphors to talk about abstract (less tangible) concepts. For example, a deadline can be "far away." Literature on SDT has traditionally employed spatial distance rather than temporal distance to effectively induce a self-distanced view. This is achieved by asking people to "move away from the situation to a point where you can now watch the event unfold from a distance and see yourself in the event" (Kross & Ayduk, 2017, p. 87) or inviting them to imagine looking at themselves from a third-person perspective or viewing a situation from the perspective of a "fly on the wall" (Kross & Ayduk, 2017, p. 85). Therefore, we theorize that spatial distance, due to its tangible nature, is effective at enabling self-distancing in the case of negative experiences. Our first hypothesis reads as follows:

H1: *The negative relationship between sentiment negativity and rating is negatively moderated by spatial distance; thus, greater spatial distance strengthens this negative relationship.*

In contrast to spatial distance, temporal distance is a less tangible, abstract concept because it lacks physical or sensory information (Lackoff, 1990; Zhang & Wang, 2009). As a result, it is less effective in facilitating self-distancing. This notwithstanding, according to the central proposition of CLT, temporal distance spurs the construal of abstract images of past experiences with a focus on the bigger picture (Trope & Liberman, 2010) and thus on the positive aspects of the experience (Adler & Pansky, 2020). This, in turn, induces a positivity bias in the individual's memory because abstract memories tend to focus on the positive aspects (Fujita et al., 2006). We expect this positivity bias to be more pronounced for negative experiences than for positive experiences due to the rating-scale ceiling (Chyung et al., 2020). Therefore, we theorize that due to the lack of self-distancing and the focus on the positive aspects regarding negative experiences, temporal distance positively moderates the relationship between sentiment negativity and rating.

H2: *The negative relationship between sentiment negativity and rating is positively moderated by temporal distance; thus, greater temporal distance weakens this negative relationship.*

Figure 1 summarizes our two hypotheses in a research model.

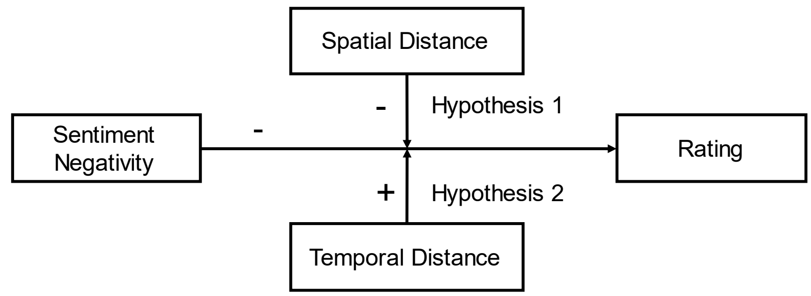


Figure 1. Research Model

Data and Methods

We obtained data from TripAdvisor using a customized web crawler. Because restaurant visits are TripAdvisor's hallmark, we focused on restaurant reviews in our study. Based on the list of counties used by Dube et al. (2010), we collected the full review history of all restaurants of 1,042 U.S. counties, covering 48 states and 4,436 cities with populations ranging from 3 people (Milford, Missouri) to 18.7 million (New York City).[2] Similar to Huang et al. (2016), we leveraged traveling behavior by reviewers as a measure of spatial distance and the difference in dates between the review publication and the consumption experience as a measure of temporal distance. Of the restaurant reviews in the data set, we included only reviews from reviewers living in one of the 4,436 collected cities. In this way, in line with prior literature (Kokkodis & Lappas, 2020), we ensured variation in traveling activity and could observe each reviewer's behavior in the absence of spatial distance.

We excluded any reviews prior to 2012 because those did not include information on the date of the restaurant visit. Our final data set included 1,206,156 individual reviews posted by 163,224 reviewers who rated 88,065 different restaurants between 2012 and 2020. Table 1 reports the summary statistics of our data set. We obtained the valence of each rating ($RATING$) and the rating history of all reviewers for the restaurants of our sample. Based on this, we computed each reviewer's average rating (REV_AVG_RATING) and review count (REV_NUM_REV) at the time of the review. Using each business's complete review history (including reviews prior to 2012), we computed its average rating (BSN_AVG_RATING) and its number of reviews (BSN_NUM_REV) at the time of review.

Main Variables

Sentiment Negativity

We used the rule-based sentiment analysis VADER, which has successfully analyzed online reviews (Hutto & Gilbert, 2014), to determine whether the consumption experience was negative overall. With the VADER implementation of the Natural Language Toolkit (Bird et al., 2009), we determined a sentence-level sentiment score, which we aggregated on the review level using the arithmetic mean. We termed the resulting variable $SENT\_NEGATIVITY$ and scaled it on a range from 1 to 5 to match it with the 5-point rating scale. Values close to 5 represent a strongly negative sentiment, and values close to 1 indicate a strongly positive sentiment, respectively.

Spatial Distance

We obtained the longitude and latitude for the center of each reviewer's home location and each restaurant location using the MapQuest API to capture spatial distance. Using these coordinates, we calculated the geodesic distance in kilometers ($TRAVEL\_DIST$) between each pair of cities (Picard, 2010). Owing to the skewness in its distribution and in keeping with prior literature (Huang et al., 2016), we log-transformed this variable after adding 1 to ensure that reviews by locals (i.e., those reviewing in their home location) were not dropped from the data set due to this transformation (LN_TRAVEL_DIST).

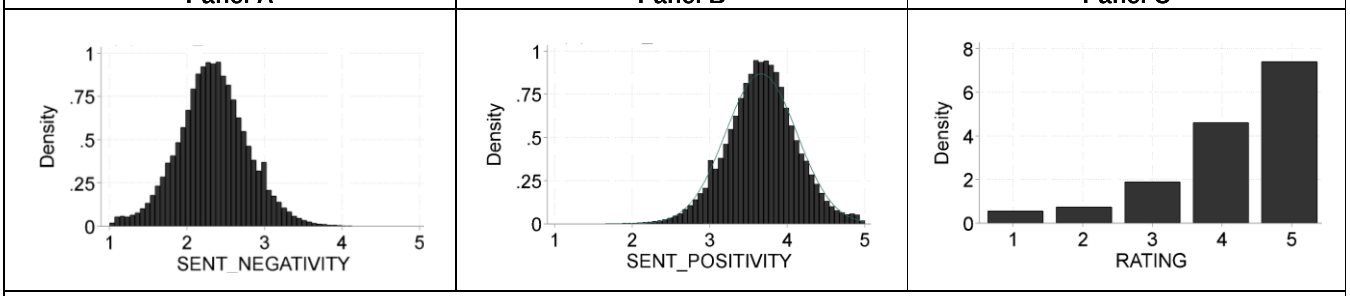
[2] Obtained from https://simplemaps.com/data/us-cities. For large cities, this database lists the populations of the metropolitan area.

Table 1. Summary Statistics

	Mean	Std. Dev.	Description
RATING	4.156	1.033	Star rating on a 5-point scale
SENT_NEGATIVITY	2.34	0.453	Negative sentiment based on the review text on a scale from 1 (positive) to 5 (negative experience)
SENT_POSITIVITY	3.66	0.453	Inverted *SENT_POSITIVITY* ranging from 1 (negative) to 5 (positive experience)
TRAVEL_DIST	375.274	787.081	Kilometers between the reviewed restaurant and the center of a reviewer's home location
RATING_SENT_DIFF	0.494	0.894	*RATING* minus *SENT_POSITIVITY*
LN_TRAVEL_DIST	3.152	2.835	Natural logarithm of *TRAVEL_DIST*
MONTH_DIFF	1.389	2.110	Number of months between the restaurant experience and the review
LN_MONTH_DIFF	0.656	0.590	Natural logarithm of *MONTH_DIFF*
BSN_NUM_REV	47.025	98.999	Number of reviews a business had at the time of the review
BSN_AVG_RATING	3.903	1.072	Average rating of a business at the time of the review
REV_NUM_REV	13.219	46.910	Number of reviews a reviewer had given at the time of review
REV_AVG_RATING	3.640	1.516	Average of all prior ratings at the time of the review

Note: For all variables *N* = 1,206,156; For first-time reviewers, *REV_NUM_REV* and *REV_AVG_RATING* are 0. Similarly, when restaurants receive their first review, *BSN_NUM_REV* and *BSN_AVG_RATING* equal 0.

Panel A	Panel B	Panel C



Note: Panel A depicts the distribution of *SENT_NEGATIVITY*; Panel B depicts the distribution of *SENT_POSITIVITY,* which we computed by inverting *SENT_NEGATIVITY*: Panel C depicts *RATING*.

Figure 2. Distributions of SENT_*NEGATIVITY*, *SENT_POSITIVITY*, and *RATING*

Temporal Distance

We measured temporal distance using information available on TripAdvisor. Because reviewers indicate the month and year of their visit on TripAdvisor, we were able to calculate a measure of temporal distance directly from our data. Following Huang et al. (2016), we calculated the difference in months between the date of the review publication and the date of the visit ($MONTH\_DIFF$). Due to the skewness of this variable's distribution, we log-transformed it after adding 1 (LN_MONTH_DIFF).

Rating

Finally, our main dependent variable was $RATING$, or the numerical rating on a scale from 1 to 5 that a reviewer gave to the restaurant experience.

Sentiment vs. Rating

Although the literature has documented a discrepancy between sentiment and rating (see Psychological Distance, Online Ratings, and Sentiment section), one would still expect a consumption experience with a high sentiment negativity to receive a low rating. This is supported by prior literature (Kim, 2021) and by the coefficient of $SENT\_NEGATIVITY$ we will later show in our analysis. However, we can also clearly see from the distributions of $SENT\_NEGATIVITY$ and $RATING$ that they do not represent the same construct. Figure 2 displays the distributions of $SENT\_NEGATIVITY$ (Panel A), $SENT\_POSITIVITY$ (Panel B), and $RATING$ (Panel C). We computed $SENT\_POSITIVITY$ by inverting $SENT\_NEGATIVITY$ to facilitate an easier comparison with $RATING$. The distribution of $RATING$ exhibits the typical skewness toward the right. The rating distribution we report is similar to the one Schoenmueller et al. (2020, p. 859) reported, which underscores the external validity of our data. By contrast, $SENT\_POSITIVITY$ exhibits less skewness, is more bell-shaped, is symmetric, and has a mean value (3.66) and standard deviation (0.453), which are substantially lower than those of $RATING$ (mean: 4.156, std: 1.033). In summary, $SENT\_POSITIVITY$ is substantially closer to a normal distribution than $RATING$ is, echoing observations in recent literature (Kim, 2021; Schoenmueller et al., 2020). This evidence also substantiates our choice for text sentiment as a measure of the negativity of an experience.

Empirical Method

To test our hypotheses, we employed the following regression model:

$$\begin{aligned} &RATING_{ijt} = \\ &\beta_0 + \beta_1 SENT\_NEGATIVITY_{ijt} + \beta_2 LN\_TRAVEL\_DIST_{ijt} \\ &+\beta_3 LN\_MONTH\_DIFF_{ijt} + \beta_4 SENT\_NEGATIVITY_{ijt} \\ &\times LN\_TRAVEL\_DIST_{ijt} + \beta_5 SENT\_NEGATIVITY_{ijt} \\ &\times LN\_MONTH\_DIFF_{ijt} + \zeta X_{it} + \xi Z_{jt} + \delta_i + \varphi_j + \theta_t + \epsilon_{ijt} \quad (1) \end{aligned}$$

$RATING_{ijt}$ represents reviewer i's rating for business j in month t. Coefficient β_1 describes the base relationship between sentiment negativity and ratings regardless of the reviewer's psychological distance. Coefficients β_2 and β_3 describe the direct relationship between spatial and temporal distance, respectively, and rating, regardless of sentiment negativity. Coefficients β_4 and β_5 represent our coefficients of interest. β_4 tests H1, and β_5 tests H2. Per our theorizing, we expected a statistically significant estimate for these coefficients with a negative sign for β_4 and a positive one for β_5.

X_{it} and Z_{jt} are vectors of reviewer-level (REV_NUM_REV and REV_AVG_RATING) and business-level (BSN_NUM_REV and BSN_AVG_RATING) control variables that serve as proxies of a reviewer's time-variant reviewing tendencies and expertise as well as a restaurant's time-variant popularity and quality. In particular, controlling for the business's average rating (BSN_AVG_RATING) prior to consumption accounts for differences in expectations that may arise from selecting a specific restaurant, as demonstrated by Yin et al. (2016). Moreover, Schoenmueller et al. (2020) validated that the number of reviews by reviewer i prior to reviewing business j serves as an effective proxy to control for rating polarity-related self-selection in reviews. We thus used REV_NUM_REV to safeguard against reviewers self-selecting into reviewing a particularly negative or positive experience.

We also implemented three-way fixed effects. First, to rule out that time-invariant unobserved reviewer characteristics were biasing our results, we introduced reviewer-level fixed effects (δ_i). These fixed effects account for reviewers' general positivity in their ratings and for their general writing style. Second, to rule out biases due to time-constant unobserved restaurant characteristics, we introduced restaurant-level fixed effects (φ_j). Third, to account for possible seasonal effects in the restaurant ratings, we used monthly and yearly fixed effects (θ_t). ϵ_{ijt} represents the random error term.

Empirical Results

Baseline Results

We estimated our multiway fixed effects regressions using the package REGHDFE for Stata (Correia, 2019). Table 2 presents our results. Column 1 presents the results from a model without interactions. Columns 2 and 3 estimate the model of Equation (1) by exclusively accounting for either spatial distance or temporal distance, respectively. Column 4 presents the coefficient estimates for the full model of Equation (1), our preferred specification. Reassuringly, we found a statistically significant and negative association between $SENT\_NEGATIVITY$ and $RATING$, which supports the validity of our operationalization for the sentiment of the consumption experience. An increase in sentiment negativity by 1 in the review text is associated with an average decrease of 1.09 in ratings. Consistent with our hypotheses, we found asymmetric moderations for the two types of psychological distance we investigated.

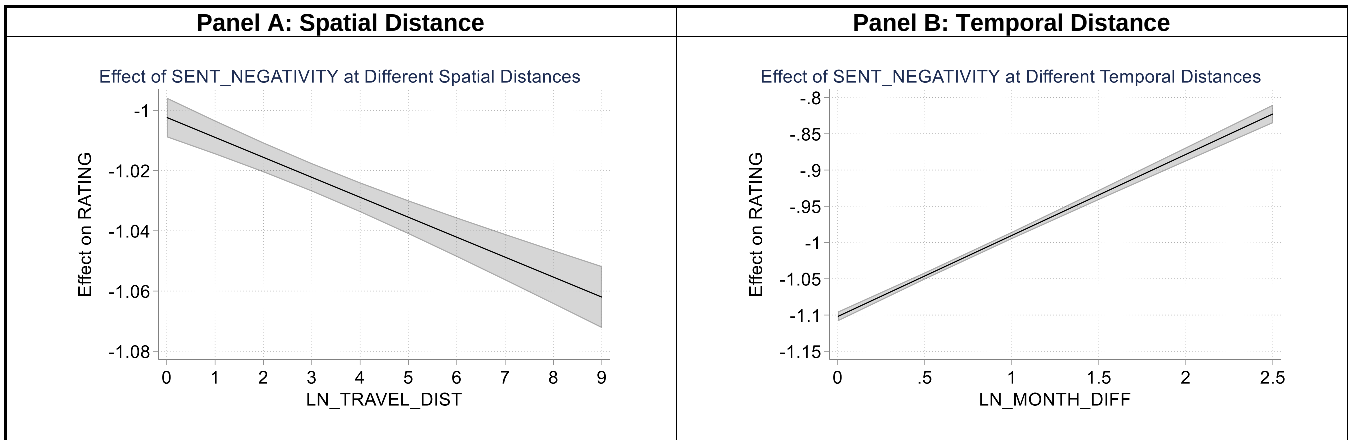
First, the statistically significant negative estimate for the interaction $SENT\_NEGATIVITY \times LN\_TRAVEL\_DIST$ supports H1. These results suggest that LN_TRAVEL_DIST negatively moderates the relationship between $SENT\_NEGATIVITY$ and $RATING$ such that it strengthens this relationship or makes it more negative when the reviewer's spatial distance increases. Second, the coefficients corresponding to temporal distance contrast these findings, as we found a statistically significant and positive coefficient for interaction $SENT\_NEGATIVITY \times LN\_MONTH\_DIFF$, which supports H2. These results suggest that LN_MONTH_DIFF positively moderates the relationship between $SENT\_NEGATIVITY$ and $RATING$ such that it weakens this negative relationship.

In summary, our analyses yielded two main results. First, an experience's sentiment as it relates to numerical evaluations is moderated by spatial distance and temporal distance. Second, the moderations of these two dimensions of psychological distance are asymmetric. We illustrate the results of the focal interactions with floodlight analyses (Spiller et al., 2013) in Figure 3. We can see that, as spatial (temporal) distance increases, the relationship between $SENT\_NEGATIVITY$ and $RATING$ becomes more negative (positive).

Table 2. Baseline Regression Results

Variable	(1) No Interactions	(2) Spatial	(3) Temporal	(4) Both
	RATING			
SENT_NEGATIVITY × LN_TRAVEL_DIST		-0.0066*** (0.00078)		-0.003*** (0.00078)
LN_TRAVEL_DIST	0.0167*** (0.00043)	0.0334*** (0.00179)		0.024*** (0.00181)
SENT_NEGATIVITY × LN_MONTH_DIFF			0.1118*** (0.00343)	0.109*** (0.00347)
LN_MONTH_DIFF	-0.0717*** (0.00164)		-0.3377*** (0.00779)	-0.328*** (0.00786)
SENT_NEGATIVITY	-1.0225*** (0.00241)	-1.002*** (0.00337)	-1.1020*** (0.00694)	-1.090*** (0.0101)
Control Variables	✓	✓	✓	✓
Reviewer-Level FE	✓	✓	✓	✓
Business-Level FE	✓	✓	✓	✓
Month and Year FE	✓	✓	✓	✓
Observations	1,206,156	1,206,156	1,206,156	1,206,156
Adj. R^2	0.426	0.425	0.426	0.427

Note: Robust standard errors are in parentheses. *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.



Note: Panel A depicts the effect of *SENT_NEGATIVITY* at different levels of *LN_TRAVEL_DIST*; Panel B depicts the effect of *SENT_NEGATIVITY* at different levels of *LN_MONTH_DIFF.* The gray area represents 95% confidence intervals.

Figure 3. Floodlight Analysis

Table 3. Overview of Theoretical Mechanisms and Mechanism Checks

Hypothesis	Theory	Explanation	Mechanism check
H1	SDT	Spatial distance is concrete and tangible and, thus, enables self-distancing for negative experiences.	Spatial distance negatively moderates the relationship between sentiment negativity and self-referential language.
H2	CLT	Temporal distance is abstract and less tangible and is, thus, less effective at enabling self-distancing for negative experiences. Hence, it spurs high construal memories, particularly for negative experiences.	Temporal distance negatively (positively) moderates the relationship between sentiment negativity and concreteness (abstractness).

Theoretical Mechanisms: How Psychological Distance is Reflected in Language

We conducted textual analyses to investigate the theoretical mechanisms underlying the observed effects and to shed more light on the asymmetry of our results regarding spatial and temporal distance. Table 3 presents an overview of the mechanisms behind our hypotheses.

Mechanism Behind H1

We established that self-distancing is responsible for the negative moderation by spatial distance. A key aspect of SDT is how individuals refer to themselves. Prior literature has established that people who use first-person words when reporting their experiences take on a more self-immersed perspective; by contrast, people who use non-first-person pronouns take on a more self-distanced perspective (Kross & Ayduk, 2017). Numerous experiments have analyzed how self-talk—the act of talking about experiences somebody had themselves—is associated with self-distancing (Kross & Ayduk, 2017). For instance, individuals using non-first-person pronouns are more likely to remember negative experiences from a distant observer's perspective than individuals using first-person pronouns (Kross et al., 2014). These individuals exhibit less emotional reactivity for negatively arousing pictures when they are associated with their name than those using first-person pronouns (Moser et al., 2017). Altogether, these findings establish that using less self-referential language, or fewer first-person pronouns, is closely tied to self-distancing.

In the context of our study, we expected the relationship between sentiment negativity and self-referential language to be negatively moderated by spatial distance. Given this moderation, the interaction between spatial distance and sentiment negativity would thus contribute to a reviewer using fewer first-person pronouns ("The food was awful" compared to "I hated the food").

To this end, we employed the Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015) to measure the usage of first-person pronouns in reviews. Based on its validated dictionary, the tool analyzes each word in a text to determine whether it is a first-person pronoun in the singular ("I," "me," "mine") or plural ("we," "us," our") and adjusts the output variable accordingly. By taking the sum of the share of singular and plural first-person pronouns, we created a new variable, $SELF\_REF$, as a measure of self-referential language. We used $SELF\_REF$ as a dependent variable instead of $RATING$ in our baseline model. According to SDT, we would expect to find that spatial distance negatively moderates the relationship between $SENT\_NEGATIVITY$ and self-referential language. The estimated coefficient for $SENT\_NEGATIVITY \times LN\_TRAVEL\_DIST$ in Column 1 of Table 4 is both statistically significant and negative. The estimates suggest that spatial distance negatively moderates the relationship between sentiment negativity and self-referential language. These findings support the existence of self-distancing as a central driver of H1. For the case of temporal distance, we found the opposite, confirming our expectation that temporal distance does not facilitate self-distancing for negative experiences.

Mechanism Behind H2

We established that CLT is responsible for the positive moderation by temporal distance. Because temporal distance is less tangible than spatial distance (Zhang & Wang, 2009), it is less effective at facilitating self-distancing; therefore, reviewers form positive high-construal memories of the past, consistent with the findings of Huang et al. (2016). Earlier work has shown that individuals' construal is reflected in their use of language (Semin & Smith, 1999), with specific words indicating either concreteness (low construal) or abstractness (high construal). To determine the construal level in review texts, we employed two measures, which we used as dependent variables.

For our first measure, we relied on the dictionary compiled by Brysbaert et al. (2014). For each word in this dictionary, an average concreteness score on a 1 (*abstract*) to 5 (*concrete*) scale is listed. For instance, words like "belief" and "hope" are abstract, whereas words like "whisky" and "tablespoon" are concrete. For each review in our sample, we calculated an average concreteness score and used this as a dependent variable (Column 2 in Table 4).

For our second measure, we used the Linguistic Category Model (LCM) (Semin et al., 2002). The LCM provides a classification scheme that assigns each text a value from 1 (*concrete representation*) to 5 (*abstract representation*) to indicate its construal level. To calculate the *LCMscore*, we followed the approach proposed by Seih et al. (2017). Five LCM categories exist: nouns, adjectives, state verbs (e.g., "loving"), interpretive action verbs (e.g., "helping"), and descriptive action verbs (e.g., "eating"). In this order, they form a linguistic continuum from abstract to concrete predicates (Seih et al., 2017). We used TreeTagger (Schmid, 1999) to identify nouns, adjectives, and types of verbs from a given sentence. After counting the number of words for each LCM category for each review, we calculated the *LCMscore* accordingly. We excluded verbs in the review texts if Seih et al. (2017) did not categorize them in their dictionary. We then used *LCMscore* as a dependent variable in our baseline model (Column 3 in Table 4).

Table 4. Self-Referential Language, Concreteness, and Abstractness as Dependent Variables

Variable	(1) Self-referential language	(2) Concreteness	(3) Abstractness
	SELF_REF	***Brysbaert Score***	***LCMscore***
SENT_NEGATIVITY × LN_TRAVEL_DIST	-0.026*** (0.00258)	0.0009*** (0.00015)	0.0003 0.00024
LN_TRAVEL_DIST	0.161*** (0.00623)	-0.0014** (0.00036)	-0.001* (0.00058)
SENT_NEGATIVITY × LN_MONTH_DIFF	0.079*** (0.01158)	-0.0068*** (0.00068)	0.00473*** (0.00111)
LN_MONTH_DIFF	-0.389*** (0.02770)	-0.001 (0.00162)	-0.017*** (0.00262)
SENT_NEGATIVITY	0.847*** (0.01402)	0.02558*** (0.00082)	-0.152*** (0.00132)
Control Variables	✓	✓	✓
Reviewer-Level FE	✓	✓	✓
Business-Level FE	✓	✓	✓
Month and Year FE	✓	✓	✓
Observations	1,206,156	1,206,156	1,206,156
Adj. R^2	0.291	0.284	0.220

Note: Robust standard errors are in parentheses. *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

According to CLT, we would expect to find a statistically significant negative (positive) moderation by the temporal distance of the relationship between sentiment negativity and concreteness (abstractness). The results in Columns 2 and 3 of Table 4 confirm these expectations. By contrast, the coefficients of the moderations by spatial distance contradict the predictions of CLT. Overall, this supports our reasoning that, for negative experiences, the moderations by temporal distance are in line with the predictions of CLT, while the moderation by spatial distance is in line with SDT.

Robustness Checks

Despite our fixed effects and control variables, lingering endogeneity concerns on the relationship between sentiment and rating may remain. There might be reverse causality such that sentiment rather than ratings change. Also, unobservable time-variant factors could affect both sentiment and rating. To mitigate these endogeneity concerns, the literature suggests a two-stage-least-square (2SLS) instrumental variable (IV) approach (Wooldridge, 2010).

To this end, we followed an approach from prior online review literature (Jabr & Zheng, 2014) and obtained the entire reviewing history of the reviewers in our data set. We used each reviewer's review sentiment regarding non-restaurants (e.g., hotels, museums, and attractions) as an IV for the independent variable $SENT\_NEGATIVITY$ based on the rationale we explain next. Reviewers have their own specific styles for writing reviews. For example, they might have an idiosyncratic enthusiasm or a neutrality in their style of writing. The reviewer-level writing style should be apparent in reviews regardless of the business category; therefore, review sentiment should be correlated across categories, satisfying the relevance criterion. However, the sentiment of a particular non-restaurant review is unlikely to correlate with the rating of a particular restaurant because they represent two separate experiences, satisfying the exclusion criterion, after accounting for reviewer fixed effects and reviewer-level control variables.[3]

To implement the IV, we computed the sentiment negativity of non-restaurant reviews the same way we did our independent variable $SENT\_NEGATIVITY$. We termed this IV $SENT\_NEGATVITIY\_NONREST$. To instrument for the interactions of $SENT\_NEGATIVITY$ and psychological distance, we followed Wooldridge (2010) and used the interaction of $SENT\_NEGATIVITY\_NONREST$ with temporal distance and spatial distance. To homogenize the IV with our endogenous variable on psychological distance, we used the mean of a reviewer's non-restaurant review sentiment in a given month in the same spatial distance as the focal restaurant review. This method is robust to possible effects that psychological distance could have on the writing style of the reviews (Li et al., 2022). To mitigate concerns of an unobserved

[3] Because writing style is idiosyncratic to specific reviewers and likely orthogonal to specific businesses, business fixed effects would represent an unnecessary restraint on the model degrees of freedom. Hence, we dropped them for more precise estimation. This did not qualitatively change our estimates compared to the results in Table 2 with business fixed effects. We present our main results without business fixed effects for reference in Table 5, Columns 1 and 3.

city-level effect influencing the sentiment of both restaurant and non-restaurant reviews, we predicted the sentiment based on a vector of cities and used this as a control variable. For temporal distance, we used the mean of a reviewer's non-restaurant review sentiment in a given year in the same temporal distance as the focal restaurant review in the specification with temporal distance. To account for this, we ran separate 2SLS models for temporal and spatial distance. To account for the time-varying appeal of a city that could change due to local events, we controlled for the monthly average sentiment of a city's restaurant ($MONTHLY\_REST\_SENT$) reviews and its non-restaurant reviews ($MONTHLY\_NONREST\_SENT$).

Following Stock and Yogo (2005), we tested the relevance of IVs in exactly identified 2SLS specifications with the first stage *F*-test of excluded instruments and the Kleibergen-Paap *rk* Wald statistic. The latter is more robust to non-i.i.d distributed standard errors (Kleibergen & Paap, 2006). Both were well above the Stock-Yogo threshold of 10% bias and the *F*-test threshold of 10 (Stock & Yogo, 2005) (temporal distance: F = 21.35, rk = 16.64; spatial distance: F = 51.43, rk = 51.08). Table 5, Columns 2 and 4, present the IV results, which are consistent with our baseline results in Table 2. Hence, our results are driven by changes in ratings, not sentiment, and are robust to omitted variable bias.

We conducted a series of further robustness checks (see the appendix) to address potential concerns regarding reviewers still traveling at the time of reviewing, the scaling of our variables, our sentiment operationalization, a correlation between propensity to post a review and psychological distance, systematic sentiment differences between psychologically close and distant reviewers, and systematically different restaurant selection by reviewers at home and while traveling. Our results remained robust to all these checks.

Further Analysis of the Discrepancy Between Ratings and Sentiment

Our baseline results have immediate implications for broader research on the relationship between a review's sentiment and its rating, which has recently received considerable attention (Kim, 2021; Schoenmueller et al., 2020). We empirically demonstrated these implications by regressing $LN\_TRAVEL\_DIST_{ijt}$ and $LN\_MONTH\_DIFF_{ijt}$ (alongside all our control variables and fixed effects from Equation 1) on the difference between ratings and sentiment (denoted $RATING\_SENT\_DIFF$, hereafter computed as $RATING - SENT\_POSITIVITY$).[4] The model is denoted in Equation (2).

$$\begin{aligned} RATING\_SENT\_DIFF_{ijt} &= \beta_0 + \beta_1 LN\_TRAVEL\_DIST_{ijt} \\ &+\beta_3 LN\_MONTH\_DIFF_{ijt} \\ &+\zeta X_{it} + \xi Z_{jt} + \delta_i + \varphi_j + \theta_t + \epsilon_{ijt} \end{aligned} \quad (2)$$

We conducted these regressions separately for each decile of $SENT\_NEGATIVITY$. In Panel A of Figure 4, we see that, as expected from our baseline results, for very high sentiment negativity (Decile 10), spatial distance did not increase $RATING\_SENT\_DIFF$. For lower levels of $SENT\_NEGATIVITY$, spatial distance significantly increased $RATING\_SENT\_DIFF$.

The most pronounced increase of the difference occurred between Deciles 5 and 9; for lower deciles, we suspect that the ratings were already high and the difference could not grow further because the rating scale capped ratings at 5.[5] These results can be explained as follows against the backdrop of our baseline results: For low $SENT\_NEGATIVITY$, spatial distance increases the ratings due to its direct effect. For very high $SENT\_NEGATIVITY$, the negative moderating effect of $SENT\_NEGATIVITY \times LN\_TRAVEL\_DIST$ offsets the increase in ratings induced by the direct effect, as predicted by SDT. Recall that our results are not explained by psychological distance affecting the sentiment. (See the Robustness Checks section and the Appendix). Therefore, changes in $RATING\_SENT\_DIFF$ are attributable to changes in $RATING$ rather than $SENT\_POSITIVITY$.

In Panel B, we see that, in line with our baseline results, temporal distance had a statistically significant negative relationship with $RATING\_SENT\_DIFF$ for reviews with low $SENT\_NEGATIVITY$. As $SENT\_NEGATIVITY$ increased, the relationship of temporal distance with $RATING\_SENT\_DIFF$ became positive, though statistically insignificant, because ratings increased relative to the sentiment. This can be explained as follows: For a given low $SENT\_NEGATIVITY$, temporal distance decreases the ratings due to its direct effect. For high $SENT\_NEGATIVITY$, the positive moderating effect of $SENT\_NEGATIVITY \times LN\_MONTH\_DIFF$ offsets the decrease in ratings due to LN_MONTH_DIFF. For very high $SENT\_NEGATIVITY$, temporal distance increases ratings, as predicted by CLT, relative to the sentiment.[6]

[4] $SENT\_POSITIVITY$ is the inverted and rescaled version of $SENT\_NEGATIVITY$ (see Sentiment vs. Rating section).

[5] We note that the average $SENT\_POSITIVITY$ of Decile 10 is 2.82 (min: 1.02, max: 3.08), whereas the average $SENT\_POSITIVITY$ of Deciles 5 to 9 is between 3.72 and 3.20. Thus, only Decile 10 captures negative experiences.

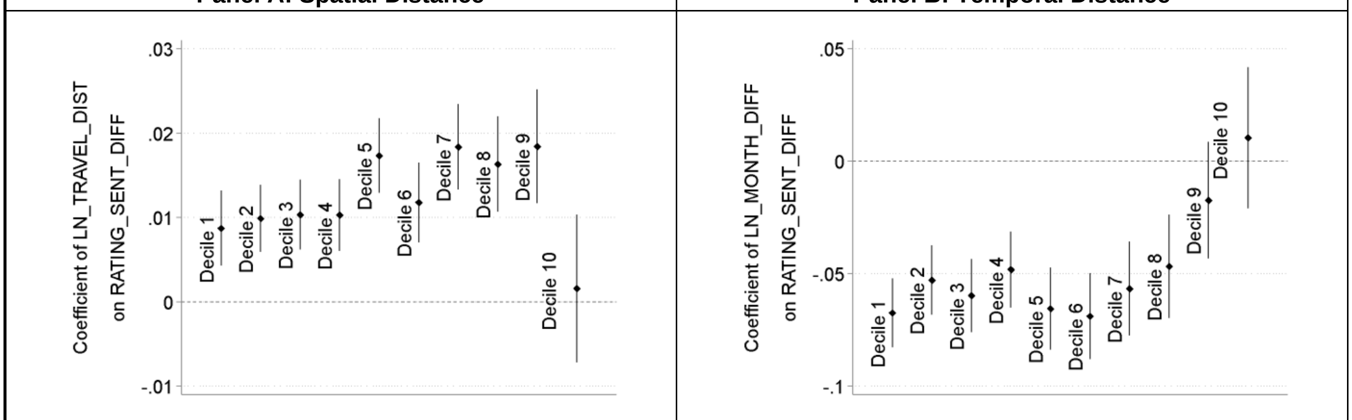
[6] We note that, due to the sample stratification by $SENT\_NEGATIVITY$ deciles and the high-dimensional fixed effects, the standard errors of the estimates in Figure 4 increase drastically. Therefore, insignificant coefficients must be interpreted with caution.

Table 5. 2SLS Regression Results

	(1) Temporal FE	(2) Temporal FE + IV	(3) Spatial FE	(4) Spatial FE + IV
Variable		*RATING*		
SENT_NEGATIVITY × *LN_TRAVEL_DIST*			-0.019*** (0.00148)	-0.0272* (0.0155)
LN_TRAVEL_DIST			0.0520*** (0.003)	0.0701* (0.036)
SENT_NEGATIVITY × *LN_MONTH_DIFF*	0.152*** (0.007)	0.131** (0.056)		
LN_MONTH_DIFF	-0.389*** (0.016)	-0.337*** (0.13)		
SENT_NEGATIVITY	-1.107*** (0.005)	-0.756** (0.324)	-0.879*** (0.008)	-0.924*** (0.194)
Control variables	✓	✓	✓	✓
Reviewer-level FE	✓	✓	✓	✓
Month and year FE	✓	✓	✓	✓
Observations	450,504	450,504	303,263	303,263
Adj. R^2	0.35	0.066	0.339	0.018

Note: Robust standard errors are in parentheses. *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Panel A: Spatial Distance | **Panel B: Temporal Distance**



Note: The deciles are taken from the distribution of $SENT\_NEGATIVITY$. Decile 1 contains reviews with a very positive sentiment, and decile 10 contains reviews with a very negative sentiment. The diamonds represent the respective estimation coefficients, and the vertical lines are 95% confidence intervals.

Figure 4. Implications of Spatial and Temporal Distance for the Discrepancy Between Rating and Sentiment

Discussion

Our goal was to deepen the understanding of how psychological distance moderates the relationship between sentiment negativity and ratings. Drawing on SDT, we introduced a novel perspective on the role of psychological distance in consumer evaluations that complements the CLT-based perspective. In an empirical study using online reviews from TripAdvisor, we found that the relationship between sentiment negativity and ratings is negatively moderated by spatial distance and positively moderated by temporal distance. We traced SDT as the driver behind the spatial distance moderation and CLT as the driver behind the temporal distance moderation.

Contributions to Theory

We provide three novel insights to research on online reviews and psychological distance.

Negative Experiences

Prior literature has clearly shown that the relationship between psychological distance and consumer evaluations is shaped by CLT (Stamolampros & Korfiatis, 2018; Huang et al., 2016). Our work reveals that CLT alone cannot fully capture online consumer evaluation behavior. With negative experiences and spatial distance, theorizing based on SDT is necessary to understand and predict online consumer evaluations. We empirically corroborate this finding by showing self-distancing behavior in review texts of negative experiences made in the context of spatial distance. Employing a continuous measure of sentiment negativity reveals new insights into the role of CLT and temporal distance. Temporal distance weakens the negative relationship between sentiment negativity and rating. This suggests that the positivity bias in ratings stemming from temporal distance found in prior literature might be particularly driven by users rating negative dining experiences higher than warranted. As per CLT, consumers reflect on negative experiences abstractly (e.g., dining with friends) and tend to neglect the annoying details of the experience (e.g., rude waiters).

Asymmetric Moderations by Spatial and Temporal Distance

Our results indicate that tangibility serves as an important differentiator of whether psychological distance fosters self-distancing or CLT behavior. We show that the more tangible psychological distance—spatial distance—is conducive to self-distancing when evaluating negative experiences. The less tangible psychological distance—temporal distance—is not conducive to self-distancing but rather fosters behavior consistent with CLT. This finding contributes to the scholarly debate (Maglio, 2020) on whether spatial and temporal distance represents a "common currency" of psychological distance (Maglio et al., 2013), providing an example of when this is not the case. In summary, our results suggest that spatial distance better supports individuals in distancing themselves from negative experiences than temporal distance does.

Relationship Between Sentiment and Rating

The relationship between a review's sentiment and its numerical rating has been an emergent theme in recent literature (Kim, 2021; Schoenmueller et al., 2020). It has been puzzling to scholars when a review's sentiment is at odds with its rating (Schoenmueller et al., 2020) or when sentiment scores and ratings exhibit distinctively different distributions (Kim, 2021). Our findings suggest that spatial and temporal distance can shape the relationship between sentiment and ratings. Our robustness checks further show that our main findings are not explained by psychological distance affecting review sentiment. Therefore, ratings rather than sentiment drive the changes in discrepancy. This raises awareness regarding the need to carefully differentiate between sentiment and rating, as they do not merely represent two sides of the same coin.

Implications for Practice

Given the importance of online reviews for consumer decision-making, and thus the success of online review platforms for local businesses, this study has several important implications for the overall market outcomes and the design of these platforms.

First, because the valence of online ratings causally leads to higher sales (Babić Rosario et al., 2016) and increased pricing power (Feng et al., 2019), biases in online review systems can substantially affect market performance. If consumers cannot reliably identify biases and account for them in decision-making, biased ratings can reduce consumer surplus (Hu et al., 2017). Consequently, both of the moderating effects of psychological distance we examine can impede consumer decision-making. With knowledge of the differential role of these biases, platform designers can adjust their review system accordingly and facilitate better consumer decision-making (Gutt et al., 2019b). By either adding further metrics (e.g., number of travelers, flagging traveler reviews) or de-biasing the average rating (Kokkodis & Lappas, 2020), platform designers can respond to deteriorations in market outcomes stemming from these biases and prevent decreases in consumer surplus.

Second, platform designers should account for these differential biases in their review elicitation strategies. For instance, Google asks consumers for reviews after they have used Google Maps to reach a business. Platforms need to be aware that ratings are systematically different depending on both the current geographical distance and the temporal distance to the experience.

Third, our results emphasize the fundamental importance of considering the review sentiment score next to the rating because it can contain more nuanced and unbiased information. For instance, businesses should compare themselves to competitors in terms of not only the rating but also the sentiment score distribution. Prior literature has suggested that third-party stakeholders, such as banks, map the competitive environment in local markets using numerical ratings (Gutt et al., 2019a). We highlight that valuable insights can be gained by doing this for sentiment scores to avoid biases relating to spatial or temporal distance.

Finally, online review systems today have broadly adopted mechanisms to modify or truncate the average rating displayed for a business or seller. For instance, platforms like TripAdvisor and Amazon employ sophisticated models instead of a simple average. Our results suggest that the difference between sentiment and numerical rating can be an important factor in de-biasing average ratings. Hence, this would be an important input factor for such models.

Limitations

Naturally, this study is not without limitations. First, even though our reliance on focal constructs derived from review texts entailed several advantages, it also had some drawbacks. With the data available, we could not observe the consumers' feelings *during* the experience and had to rely on sentiments reported in the review text. Although it is reasonable to expect that the direction of an experience's sentiment will persist until the time of review writing (in other words, an awful restaurant experience is unlikely to be viewed as an overall positive experience at the time of writing), there may be finer nuances of the experience that we could not measure. Second, although we used granular data on spatial and temporal distance, we could not exactly determine the reviewers' location during the time of review writing. Despite our robustness checks (see the Appendix), some travelers could have reviewed the restaurant in spatial proximity.

Future Research

Based on our results, we glean two promising avenues for future research. First, future research could examine the tangibility of psychological distance in more detail. While we dichotomized this construct, there may be finer-grained differences in tangibility. Moreover, future research could elucidate the tangibility of social and hypothetical distance. Second, given the interdisciplinary interest in psychological distance, future research could investigate the relationship between psychological distance and self-distancing in further domains beyond consumer evaluations, such as negotiation, where temporal distance manifests in asynchronous communication and spatial distance in virtual meetings.

Conclusion

This study advances the understanding of psychological distance in online reviewing behavior. It suggests that theorizing about digitized consumer evaluations in the presence of spatial distance should also draw on SDT, rather than solely on CLT, and consider the tangibility of psychological distance, especially for negative experiences. To the best of our knowledge, we are the first to find asymmetric moderating effects of spatial and temporal distance in consumer evaluation behavior. Altogether, this study draws a broader picture of psychological distance in online reviewing behavior.

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Appendix

Table A1. Additional Robustness Checks

Concern	**Robustness checks**
Reviewers are still at the travel destination when reviewing	Reestimating our baseline model with a sample restricted to *MONTH_DIFF > 0*
Scaling of our variables	Mean centering *LN_TRAVEL_DIST* and *LN_MONTH_DIFF*
Loss of observations from dropping all reviews with a temporal difference greater than 0	Reestimating our baseline model with a triple interaction between *LN_TRAVEL_DIST, NEGATIVITY*, and a binary variable indicating whether MONTH_DIFF > 0
Inaccurate operationalization of sentiment	Alternative operationalization using the average negativity score of all sentences as determined by SentiStrength (Thelwall, 2017)
Correlation between propensity to post a review and psychological distance	Undersampling of spatially distant reviewers who give negative ratings and temporally distant reviewers who give positive ratings
Sentiments of psychologically close and distant reviewers are systematically different	Reestimating our baseline model using only clear-cut positive and negative sentiment, which psychological distance is less likely to affect
Reviewers select different restaurants when traveling than at home, possibly due to TripAdvisor website changes	Reestimating our baseline model with reviewer-restaurant chain fixed effects on a sample of only chain restaurants to ensure that reviewers visit the same restaurants at home and while traveling