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What Drives Consumers to Post More Visual Contents in Online Reviews? A Trait Activation Theory Perspective

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What Drives Consumers to Post More Photos in Online Reviews? A Trait Activation Theory Perspective

Abstract

Purpose: This study aims to investigate the influence of the reviewed establishment's price level and the user's social network size and reputation status on consumers' tendency to post more visual imagery content. Furthermore, it explores the moderating effects of user experiences and geographic distance on these dynamics.

Design/methodology/approach: This study adopts a multi-method approach to explore both the determinants behind the sharing of user-generated photos in online reviews and their internal mechanisms. Using a comprehensive secondary data set from Yelp.com, the authors focused on restaurant reviews from a prominent tourist destination to construct econometric models incorporating time-fixed effects. To enhance the robustness of the authors' findings, the authors complemented the big data analysis with a series of controlled experiments.

Findings: The reviewed establishments price level and the users reputation status and social network size incite corresponding motivations conspicuous display "reputation seeking" and social approval motivating users to incorporate more images in reviews. "User experiences can amplify the influence of these factors on image sharing." An increase in the users geographical distance lessens the impact of the price level on image sharing, but it heightens the influence of the users reputation and social network size on the number of shared images.

Practical implications: As a result of this study, high-end establishments can increase their online visibility by leveraging user-generated visual content. A structured rewards program could significantly boost engagement by incentivizing photo sharing, particularly among users with elite status and extensive social networks. Additionally, online review platforms can enhance users' experiences and foster more dynamic interactions by developing personalized features that encourage visual content production.

Originality/value: This research, anchored in trait activation theory, offers an innovative examination of the determinants of photo-posting behavior in online reviews by enriching the understanding of how the intricate interplay between users' characteristics and situational cues can shape online review practices.

Keywords: Online review, Visual imagery content posting, Trait activation theory, User experience, User geographical distance, Visual content posting

Paper type: Research paper

1. Introduction

In the digital age, consumer decision-making is heavily influenced by online reviews, with a staggering 93% of consumers consulting them before purchases (Valtonen, 2023). Reviews have evolved beyond mere validation, becoming essential for businesses as 58% of consumers are willing to pay more or travel further for businesses with positive reviews. Visual elements such as photos and videos play a significant role in this context, with 62% of consumers more likely to make a purchase when visuals from other customers are available (Valtonen, 2023). This shift toward visual testimonials is transforming purchasing decisions, with evidence showing that reviews featuring photos enhance engagement and impact purchase intentions more than text alone (Li and Xie, 2020). Further, Kwak *et al.* (2023) integrate perceptions of both reviewers and readers toward negative online reviews, offering insights into customer decision-making influenced by visual and textual content. Given the increasing significance of visual content, our study extends Sheng's (2019) notion of engagement, traditionally linked to writing reviews, to also include the quantity of user-generated photos within online reviews. This expanded view of engagement acknowledges that both textual and visual elements contribute to the depth of customer interactions with brands or firms online, enhancing the expressive richness of these exchanges.

This visual impact is particularly pronounced in tourism and hospitality (Li *et al.*, 2022a, 2022b), where experiences are inherently experiential, making photos invaluable for conveying ambiance, decor and sensory richness (Zhang *et al.*, 2019; Oliveira and Casais, 2019) highlighted the importance of user-generated photos in the hospitality industry, showing how they significantly affect restaurant selection and influence customer choices. Despite the importance of review photos, a gap exists due to the voluntary nature of posting (Huang *et al.*, 2019), making it crucial to understand the drivers behind photo sharing in reviews. While there is extensive research on user-generated textual content (Huang *et al.*, 2019; Zhang *et al.*, 2014), the motives behind photo sharing are less understood. Studies have explored photo-sharing motivations on social media across platforms and contexts (Cho *et al.*, 2019; Li, 2019), but specific drivers for including visual content in online reviews are underexplored. Hu *et al.* (2022) and An *et al*. (2020) have provided some insights, particularly in specific contexts like travel or luxury hotels, but these findings are limited and context-dependent. Moreover, the existing literature does not fully explore how these influencing factors may vary across heterogeneity consumer groups, leaving a gap in our understanding of the nuanced dynamics in online review photo sharing.

Our study uses trait activation theory (TAT; Tett and Burnett, 2003) to explore a broader array of determinants influencing photo sharing in online reviews. By applying TAT, we examine how digital contexts serve as situational cues that activate personal traits, leading to visual content sharing. This approach helps us delve into the individual-environment interaction, extending TAT's application to consumer online behavior. We aim to address three research questions:

*RQ1.*What factors contribute to sharing visual content in online reviews?

*RQ2.*What mechanisms underlie these influencing factors?

*RQ3.*How do contextual factors shape the influence of these determinants on visual content sharing?

Building on Hu *et al.* (2022) and An *et al.* (2020), we extend the inquiry to explore how a business's price level affects the number of photos shared in reviews, examining conspicuous display as an underlying mechanism. Informed by TAT, our research investigates how task-level and social-level cues, such as the size of a user's social network and reputation status, serve as significant drivers for sharing more visual content. We also introduce user experience and geographic distance as moderators, examining their impact on the relationship between determinants and photo-sharing behavior. Our multi-method research approach combines econometric modeling of secondary review platform data to pinpoint key factors affecting photo sharing and their limits, with experimental designs investigating the psychological underpinnings of photo sharing through concepts like conspicuous display, social approval and reputation seeking. This study further advances online photo sharing behavior understanding by highlighting the moderating roles of user experience and geographic distance. These insights enrich theoretical perspectives and offer practical strategies for businesses to enhance customer engagement through visual content.

2. Literature Review

2.1 Online review and photo-sharing behavior

Online reviews serve as a key component of electronic word-of-mouth (eWOM), distinguished by their context-specific nature, often linked to particular experiences or products (King *et al.*, 2014). Unlike the broad, relationship-driven content on social media platforms like Facebook or Twitter, online reviews focus on sharing authentic personal experiences, mainly on platforms where potential buyers seek insights for informed decision-making (Hu *et al.*, 2022). Increasingly, these reviews not only include textual content but also visual elements like photos and videos, recognizing the enhanced persuasive power of imagery in complementing narratives. Zinko *et al.* (2020) noted the significant role of images in influencing consumer behaviors such as purchase intention and trust, particularly for hedonic products.

Recent studies have delved into the dynamics of user-generated images in online reviews and their impact on customer engagement. Li *et al.* (2024) conducted a comprehensive panel data analysis, highlighting how user-generated images boost consumer interactions and engagement with online content. Similarly, Tang *et al.* (2022) found that photo-sharing in reviews correlates with more positive evaluations of tourism products, mediated by the emotion of pleasure. Ma *et al.* (2023) further explored the predictive power of user-generated images on online travel agency platforms for tourism demand forecasting, emphasizing the utility of visual content in anticipating tourism trends. The influence of visual cues on consumer behavior has been expanded upon by Kwak *et al.* (2023), who integrated reviewers' and readers' perceptions of negative online reviews, and Law *et al.* (2023), who highlighted the potential of artificial inteligence in analyzing both textual and visual review content. Zhao *et al.* (2024) applied an improved Kano model to classify travelers' requirements from online reviews, demonstrating the analytical value of visual content.

Moreover, the research has explored how factors like geographic origin and gender (Pabel and Cassidy, 2023), humor styles (Hasan *et al.*, 2021) and cultural nuances (Mattison Thompson and Brouthers, 2021) affect photo-sharing behavior and digital consumer engagement. These studies underline the complex interplay between textual and visual eWOM, where visual content not only adds an emotional and experiential dimension to reviews but also poses questions regarding the determinants of visual content sharing and the psychological drivers behind such behavior. Despite recognizing the impact of visual content in eWOM, there remains a gap in understanding the specific factors and internal mechanisms influencing consumers to share more visual content, a gap our study aims to address.

2.2 Online photo-sharing behavior and motivations

The proliferation of image-centric social media platforms has intensified interest in photo-sharing behaviors and motivations, with images playing a crucial role in consumer decision-making by providing rich information beyond textual descriptions (Li *et al.*, 2023; Li and Xie, 2020). A diverse range of motivations for photo sharing, identified through various research methodologies, is summarized in Appendix 1, available in supplementary material to article, categorizing studies by their methodological approaches.

Interview-based studies have shed light on motivations such as self-expression, self-presentation and social connection (Cho *et al.*, 2019; Oeldorf-Hirsch and Sundar, 2016). Similarly, Wang *et al.* (2017) revealed motivations like social and relational interactions, self-image projection and emotion expression in the context of travelers sharing food experiences on social media. Survey-based research has significantly enhanced understanding of online photo sharing. For example, Prado-Gascó *et al.* (2017) highlighted motivations like information sharing, entertainment and fanship in social media, while Hunt *et al.* (2014) examined photo-messaging through lenses like technology acceptance and diffusion, emphasizing factors like technology adoption, self-expression and self-presentation. These motivations vary across platforms, with research indicating different drivers for photo sharing on platforms like Facebook (Malik *et al.*, 2016; Stefanone *et al.*, 2011) and Instagram (Lee *et al.*, 2015), as well as specialized sites like Flickr (Nov *et al.*, 2010). Mixed methods research, like that of Li (2019), and studies using big data (Hu *et al.*, 2022; An *et al.*, 2020) have provided broader insights, exploring motivations ranging from recognition and enjoyment to self-enhancement and the influence of luxury or satisfaction on photo sharing in reviews.

Despite these contributions, research gaps remain. Most studies have focused on the binary aspect of photo presence in reviews, with less attention given to the factors affecting the quantity of shared photos, which could offer deeper insights into user engagement (Hu *et al.*, 2022; An *et al.*, 2020). Moreover, the mechanisms driving active visual content sharing, and how these compare to motivations for textual content, are underexplored. While broad motivational theories have been frequently applied, they may not fully capture the nuanced dynamics of photo sharing in specific contexts. The interplay between contextual factors and personal traits, and the influence of situational cues on motivations, remain areas for further investigation, suggesting a potential application for theories like TAT to illuminate context-specific motivations and behaviors.

2.3 Trait activation theory

TAT (Tett and Burnett, 2003) proposes that specific situational stimuli can trigger or suppress particular traits, thus affecting participation in social media activities such as generating and sharing user-generated content (Li and Xie, 2020). Originating from interactive psychology, TAT examines how external situations interact with internal traits to drive behavior (Blumer, 1986), suggesting that latent traits are activated by relevant situational cues, leading to predictable behaviors (Wihler *et al.*, 2017). Essentially, TAT suggests personality traits, as dormant tendencies, are expressed when triggered by appropriate cues (Tett and Guterman, 2000). TAT, widely used in organizational behavior, examines how personal traits interact with situational stimuli to influence behavior. Tett *et al.* (2021) highlight that TAT considers both task-level and social-level cues crucial for trait activation. Task-level cues, related to the demands of a task, can motivate actions to meet these demands, such as platforms encouraging users to include photos with reviews (Penney *et al.*, 2011). Social-level cues, on the other hand, relate to interactions within social networks that allow for the expression of personality traits (Pérez-Fernández *et al.*, 2022), where a user's large social network might lead to frequent photo sharing in reviews. An individual's actions within a social network often reflect their unique personality traits. For example, a user with a vast social network – indicative of a strong social presence – may share photos frequently in online reviews. Applications of TAT are evident in social contexts such as classroom team pairings (Anderson and Tett, 2006), and employee promotability assessments (Zhang *et al.*, 2022), among others. This study aims to broaden the theoretical comprehension of TAT within cyber environments, which may differ from traditional physical settings. It postulates that in the context of review photo-posting, environmental externalities activate certain individual traits, prompting users to post more photos with text reviews, consequently generating intrinsic rewards.

3. Research hypotheses

3.1 Influence of price level on review photo sharing

The "snob effect" suggests that higher-priced items are seen as more exclusive, leading to conspicuous consumption where individuals showcase their status by purchasing high-status goods (Gilady, 2018; Hu *et al.*, 2022). In hospitality, prices signal social status, with luxury establishments perceived as more prestigious (Hung *et al.*, 2010; Barrera and Ponce, 2021). Social comparison theory indicates people share such experiences to highlight their status, potentially boosting self-esteem (Loureiro *et al.*, 2020). Photos in reviews can enhance this effect, providing a vivid representation of the experience and increasing visibility (Atwal *et al.*, 2018; Lee *et al.*, 2015). Moreover, TAT suggests that certain situations activate specific traits, leading to related behaviors (Wihler *et al.*, 2017). In this context, sharing photos from high-end venues on social media may seek social recognition. The establishment's price level serves as a cue that triggers conspicuous display traits, increasing the likelihood of photo sharing with reviews to signal status. Thus, we hypothesize the following:

H1. The price level of the reviewed establishment positively impacts the number of photos shared in online reviews.

3.2 Users' social network size and review photo sharing

TAT suggests that social networks act as "social-level cues," triggering the need for social approval, a key motivator for behaviors like content sharing (Tett and Guterman, 2000; Wihler *et al.*, 2017). This need for approval drives users to post content, such as reviews and photos, seeking positive feedback from their network. Larger social networks amplify this effect, as a broader audience increases the chances of receiving approval, motivating users to share engaging content (Zhao *et al.*, 2008). Furthermore, research shows that individuals with extensive social networks are more likely to contribute content, driven by desires for social presence, reputation enhancement, or validation (Marengo *et al.*, 2021; Wang *et al.*, 2021). Given that photos often elicit more engagement than text, users seeking approval may prefer to share images with their reviews (Yim *et al.*, 2021). The affirmation from social networks reinforces the photo-sharing behavior, particularly among users with many connections. Hence, we hypothesize the following:

H2. Users social network size (i.e., number of friends) positively impacts the number of photos shared in online reviews.

3.3 Users' reputation status and review photo sharing

Online review platforms use features like elite badges to signify a user's reputation and credibility (Lampel and Bhalla, 2007), which is typically earned through valuable contributions (Bolton *et al.*, 2004). Such reputation can increase user engagement and the tendency to post reviews, with high-reputation users often benefiting from their status (Banerjee *et al.*, 2017). According to TAT, reputation serves as both a social and task-level cue; socially, it positions users as influencers, enhancing the impact of their reviews (Ping *et al.*, 2022), and on a task level, it sets expectations for content quality (Zhang *et al.*, 2020). High-status users may thus add photos to their reviews to provide a comprehensive view and uphold their reputation. We hypothesize the following:

H3. Users reputation status (i.e., elite badge) positively influences the number of photos shared in online reviews.

3.4 Moderating role of user experience

TAT indicates that positive experiences can activate behavioral responses (Tett and Guterman, 2000), with satisfaction, reflected in review ratings, often representing user experience (Li *et al.*, 2019). High satisfaction encourages experience sharing for social validation and personal expression (Hennig-Thurau *et al.*, 2004). Drawing upon legitimacy theory, Invernizzi *et al.* (2022) highlights how organizations strategically use visual content to influence stakeholder perceptions. This perspective can be extended to analyze why individual consumers who, through their online reviews, use photos as a means to enhance the perceived legitimacy and appeal of their experiences. Therefore, a positive user experience might intensify the urge to share more photos, highlighting satisfaction or enhancing the experience's appeal.

A good user experience may prompt conspicuous display, especially with high-priced experiences, to showcase social status (Berger and Ward, 2010). Sharing photos enriches the narrative of premium experiences (Atwal *et al.*, 2018), emphasizing the effect of establishment price on photo sharing. Furthermore, positive experiences can heighten a user's desire to influence others' choices and contribute meaningfully to their social network (Cheung and Lee, 2012). As a result, users with extensive social networks may feel a heightened impulse to share more photos in their reviews, using their influence to recommend establishments and express satisfaction. For elite users, sharing a greater number of photos within their reviews can consolidate their reputation status and display their ability to distinguish and appreciate superior experiences (Cheung and Lee, 2012). This can further augment the influence of their elite status on the number of photos shared in online reviews. Thus, we hypothesize the following:

H4a. Consumer experience enhances the positive impact of reviewed establishment price level on the number of photos shared in online reviews.
H4b. Consumer experience enhances the positive impact of user social network size on the number of photos shared in online reviews.
H4c. Consumer experience enhances the positive impact of user reputation status on the number of photos shared in online reviews.

3.5 Moderating role of user distance

In tourism, distance encompasses both physical and psychological aspects, affecting travelers' engagement and perception of experiences (Lee and Kim, 2020; Park *et al.*, 2019). The effort and resources required for long-distance travel enhance the perceived value of experiences, motivating travelers to share their journeys (Yang *et al.*, 2023). According to construal level theory, distant experiences are seen as more abstract and significant, potentially making them seem more exclusive (Trope and Liberman, 2010). This perceived exclusivity may amplify the effects of factors like establishment price, social network size and reputation status on photo-sharing. Tourists, viewing their long-distance experiences as unique, could be more inclined to share photos compared to locals, highlighting the exclusivity of their visits (Berger and Ward, 2010; Toubia and Stephen, 2013; Cheung and Lee, 2012). This leads to the hypothesis that user distance intensifies the impact of these factors on the propensity to share more photos. Based on this:

H5a. User distance enhances the positive impact of reviewed establishment price level on the number of photos shared in online reviews.
H5b. User distance enhances the positive impact of user social network size on the number of photos shared in online reviews.
H5c. User distance enhances the positive impact of user reputation status on the number of photos shared in online reviews.

On this basis, the framework guiding this study is proposed (see Figure 1).

Insert Figure 1 Here

4. Methodology and Results

Our methodology combined quantitative techniques, including secondary data analysis and three online experiments, to ensure comprehensive and reliable findings, addressing the limitations of single-method approaches (Li, 2020). Initially, we analyzed a large data set of restaurant reviews to pinpoint factors affecting photo-sharing. Subsequent online experiments examined the motivations for this behavior.

4.1 Study 1: Secondary Yelp Data Modeling

4.1.1 Data

Our study used data from Yelp.com, focusing on a diverse sample of Las Vegas restaurants, chosen for their global culinary appeal. Data spanning January 2005 to February 2021 encompassed review content, restaurant details and user profiles from 300 restaurants, with 401,126 reviews analyzed, 26.23% of which included photos. A comprehensive descriptive analysis of the data set can be found in Appendix 2, available in supplementary material to article.

4.1.2 Variable Operation and Summary Statistics

The dependent variable $RewPhotos_{ijk}$ was quantified as the aggregate number of photos within a specific review. The independent variables were $ResPrice_j$, $UserFriends_k$, and $UserElite_{ik}$, denoting restaurant price level, user social network size, and user elite status, respectively. To further delineate the conditions for photo sharing behavior, we considered user experience ($RewRating_{ijk}$) and user distance ($UserDistance_{jk}$) as moderating variables, respectively. Calculation of user geographic distance can be found in Appendix 3, available in supplementary material to article.

In consideration of potential confounders, we integrated control variables shown by previous studies to impact online review behavior. These encompass review-specific, user-specific, restaurant-specific and time-specific variables. Detailed operationalization of variables and descriptive analysis of our variables can be found in Table 1 and Appendix 2, available in supplementary material to article.

Insert Table 1 Here

4.1.3 Econometric Model Specification

Recognizing the nature of our dependent variable, RewPhotos, a count variable, we initiated our analysis with a poisson regression to explain our dependent variable (Hilbe, 2014). Further, in consideration of the individual effects across our extensive user base, which spans over several hundred thousand, we opted for a Poisson Pseudo-Maximum Likelihood (PPML) regression model using high-dimensional fixed effects (Correia *et al*., 2019) to investigate the influence of the reviewed establishment's price level and the user's social network size and reputation status on consumers' behavior of posting more visual imagery contents in the context of online reviews. This approach is advantageous for controlling individual heterogeneity in large datasets and is particularly suitable for count data with overdispersion, as is the case with our dependent variable, *RewPhotos*. The PPML model accounts for the excess zeros and overdispersion, offering a more robust alternative to negative binomial regression for our high-dimensional data structure (Cameron and Trivedi, 2013; Silva and Tenreyro, 2006; Correia *et al*., 2019).

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Preliminary estimation steps involved checking the data sets for normality and outliers. To minimize potential bias from extreme values, we applied winsorization to all continuous variables at both the lower and upper extremes, specifically at the 1st and 99th percentiles (Ham *et al.*, 2018). In addition, given the observed skewness and kurtosis in the distribution of *RewPhotos*, and similarly skewed distributions of *UserElite*, *UserDistance*, *Restaurant popularity*, *Peer influence*, *User posted reviews*, *User posted photos* and *Review readability*, we applied a natural logarithmic transformation to these variables to approximate normal distributions. This methodological adjustment is in line with Mariani and Borghi (2018), who suggest that transformations are necessary for review distributions to achieve a more normalized distribution, essential for accurate regression modeling. This transformation is necessary to mitigate the influence of extreme values and outliers, allowing for more accurate regression modeling. Moreover, we incorporated user experience (gauged by review rating) and user geographical distance as moderators. The resultant econometric model is outlined as follows:

$$RewPhotos_{ijk} = \exp\big(\beta_{10} + \beta_{11}ResPrice_j + \beta_{12}RewrElite_{ik} + \beta_{13}LogUserFriends_k + \beta_{14}Control_i + T_t + M_{ij} + U_k + \varepsilon_{1,ijk}\big) \quad (1)$$

$$RewPhotos_{ijk} = \exp\,(\beta_{20} + \beta_{21}ResPrice_j + \beta_{22}RewrElite_{ik} + \beta_{23}LogUserFriends_k + \beta_{24}RewRating_{ijk} + \beta_{25}ResPrice_i \times RewRating_{ijk} + \beta_{26}RewrElite_{ik} \times RewRating_{ijk} + \beta_{27}LogUserFriends_k \times RewRating_{ijk} + \beta_{28}Control_i + T_t + M_{ij} + U_k + \varepsilon_{2,ijk}) \quad (2)$$

$$RewPhotos_{ijk} = \exp(\beta_{30} + \beta_{31}ResPrice_j + \beta_{32}RewrElite_{ik} + \beta_{33}LogUserFriends_k + \beta_{34}UserDistance_{jk} + \beta_{35}ResPrice_i \times UserDistance_{jk} + \beta_{36}RewrElite_{ik} \times UserDistance_{jk} + \beta_{37}LogUserFriends_k \times UserDistance_{jk} + \beta_{38}Control_i + T_t + M_{ij} + U_k + \varepsilon_{3,ijk}) \quad (3)$$

4.1.4 Results of Empirical Models

Table 2 reveals factors influencing the quantity of photos accompanying reviews, encompassing year and month fixed effects. Table 2 shows a positive link between restaurant price level (*ResPrice*) and photo sharing, with coefficients from 0.179 to 0.230, indicating more photos are shared for higher-priced restaurants. User elite status (*UserElite*) also correlates with increased photo sharing, with coefficients from 0.409 to 1.183. Similarly, users with larger social networks (*UserFriends*) tend to share more photos, with coefficients from 0.107 to 0.241. These findings, supported by fixed effects and user-level clustering to adjust for potential biases, confirm hypotheses *H1*, *H2* and *H3*. Further, the findings are consistent across various models, which also account for time-related variations, enhancing the robustness of our results.

Insert Table 2 Here

Table 3 shows that user satisfaction (*RewRating*) enhances the effect of restaurant price, social network size and elite status on photo sharing, with coefficients of 0.063, 0.010 and 0.191 respectively, all significant at $p < 0.01$. Distance from the restaurant (*UserDistance*) moderates these relationships differently, reducing the impact of restaurant price (coefficient −0.007, $p < 0.01$) while amplifying the influence of social network size and elite status (coefficients 0.003 and 0.036 respectively, $p < 0.01$), thus partially supporting our hypotheses. Specifically, *H5a* is rejected, whereas *H4a–H4c* and *H5b–H5c* are supported. Please see Appendix 4, available in supplementary material to article, for detailed results.

Insert Table 3 Here

4.1.5 Robustness Tests

For robustness, we first applied a logarithmic transformation to photo counts and analyzed pre-pandemic data, ensuring consistency across various model specifications and timeframes. Second, we isolated the data to a pre-pandemic period to mitigate the confounding effects of COVID-19 on user behaviors. These steps, suggested by Filieri et al. (2023), confirmed the stability of our results, as detailed in Appendix 5, available in supplementary material to article, enhancing their credibility.

4.2 Study 2: Experiments

To explore how conspicuous display, social approval and reputation seeking mediate the impact of establishment price, social network size and reputation status on photo-sharing in online reviews, we conducted three preliminary tests to validate our experimental materials (see Appendix 6, available in supplementary material to article). Following this validation, we carried out three experiments focused on these mediators.

4.2.1 Experiment 1: Reviewed Establishment Price Level

4.2.1.1 Participants and procedure

Experiment 1 explored how the price level of a reviewed establishment affects photo-posting behavior, with 110 Mturk workers participating (M_{age} = 35.6, 43% female). Participants were assigned to scenarios representing different price levels (budget, mid-range, high-end) and asked to envision visiting a restaurant in their assigned category (see Appendix 6, available in supplementary material to article). They then viewed a mock Yelp page indicative of the restaurant's price level and wrote a review. Participants also assessed their conspicuous display tendency using a 13-item scale and indicated the number of photos they would include in their review. Demographic information was collected at the end.

4.2.1.2 Manipulation check and measurement

Participants accurately recognized the intended price levels, confirming the effectiveness of our price level manipulation ($M_{\_budget}$ = 3.38, $M_{\_mid\text{-}range}$ = 5.70, $M_{\_high\text{-}end}$ = 5.83, F = 48.96, p < 0.01). The conspicuous display scale demonstrated high reliability (α = 0.96).

4.2.1.3 Results

A one-way ANOVA results showed significant differences in the number of photos participants planned to share across price levels (F (2,107) = 17.81, p < 0.01), with those in the high-end scenario reporting a higher propensity to share photos. The mediation effect of conspicuous display was analyzed using Hayes' (2013) bootstrapping method. The analysis showed that conspicuous display significantly mediated the effect of restaurant price level on number of photos shared (indirect effect = 0.98, 95% CI [0.54, 0.1.46]), indicating partial mediation, as the direct effect of price level remained significant (1.02, 95% CI [0.48, 1.56]). These results support that conspicuous display plays a mediating role in the relationship between restaurant price level and photo-sharing behavior in online reviews.

4.2.2 Experiment 2: User Social Network Size

4.2.2.1 Participants and procedure

Experiment 2 focused on how social network size affects photo sharing in online reviews, considering the need for social approval as a mediator. 112 Mturk workers participated, with an average age of 35.46 and 20% being female. After reading informed consent, they were assigned to small, medium, or large social network profiles and instructed to write a mock review as if the profile were their own (see Appendix 6, available in supplementary material to article). They then proceeded with tasks designed to measure their perceived need for social approval (Crocker *et al.*, 2003) and the number of photos they intended to post, followed by demographic questions.

4.2.2.2 Manipulation check and measurement

Manipulation checks confirmed participants accurately perceived the assigned social network sizes ($M_{\_small}$ = 5.19, $M_{\_medium}$ = 5.53, $M_{\_large}$ = 5.85, F = 4.48, $p < 0.05$). The reliability of the social approval scale was high (α = 0.95), ensuring dependable measurement.

4.2.2.3 Results

The ANOVA results indicated a significant effect of user social network size on the number of photos shared ($F (2,109) = 37.74$, $p < 0.01$), with those in larger network conditions indicating a greater likelihood to share photos. Hayes' bootstrapping confirmed the need for social approval as a significant mediator, with both the mediating (indirect effect = 0.84, 95% CI [0.40, 1.25]) and direct effects (direct effect = 1.56, 95% CI [1.27, 1.86]) indicating partial mediation. This indicates that the need for social approval serves as mediator, amplifying photo-sharing behavior among users with more extensive social networks.

4.2.3 Experiment 3: User Reputation Status

4.2.3.1 Research design and procedure

Experiment 3, featuring 109 Mturk workers in a between-subjects design, investigated how user reputation status (elite vs. non-elite) influences photo-sharing in online reviews, with a focus on the mediating role of reputation seeking. Participants, after an introduction to the study's objectives, were assigned to one of two reputation scenarios and interacted with a mock Yelp profile indicating elite or non-elite status (see Appendix 6, available in supplementary material to article). They rated their perceived reputation status, their intention to post photos and their reputation seeking needs (three-items scale, Wasko and Faraj, 2005), followed by demographic questions for control purposes.

4.2.3.2 Manipulation check and measurement

Participants accurately recognized their assigned reputation status, with elite users perceived as having a higher reputation ($M_{\_elite}$ = 5.78) compared to non-elite ($M_{\_non\text{-}elite}$ = 3.95; $t = 11.19$, $p < 0.01$), validating the manipulation. The scale for measuring reputation-seeking behavior showed high reliability ($\alpha = 0.90$).

4.2.3.3 Results

An independent sample test results showed a significant effect of reputation status on photo-sharing ($t = 4.06$, $p < 0.01$), with elite users more inclined to share photos ($M_{\_elite}$ = 6.50) compared to non-elite users ($M_{\_non\text{-}elite}$ = 4.25). Hayes' bootstrapping method indicated that reputation seeking significantly mediated the relationship between reputation status and photo-sharing (indirect effect = 2.35, 95% CI [1.55, 3.15]). This experiment confirms that reputation status impacts photo-sharing behavior, partially mediated by users' reputation-seeking motivations.

5. Discussion and Implications

5.1 Conclusion and discussion

User-generated photos have become a crucial tool in digital communication, effectively encapsulating and transmitting experiences. Oliveira and Casais (2019) emphasized the impact of such imagery on consumer choices, especially in the hospitality industry. Our study builds on this foundation to explore the motivations behind photo sharing in online reviews, using data from Yelp.com and controlled experiments. We have uncovered motivations behind photo sharing, revealing that individuals at high-priced venues often share more photos not just for satisfaction but to signal socioeconomic status, echoing An *et al.* (2020). Conspicuous display emerged as a key mediator, suggesting photo sharing as a means to showcase affluent consumption.

Our findings also show that those with larger social networks are likelier to share photos, driven by a need for social approval, as supported by Cheung and Lee (2012). This behavior suggests photo sharing as a form of social capital, enhancing one's online influence (Marengo *et al.*, 2021). Additionally, elite status users frequently share photos to boost their reputation, with reputation seeking identified as a significant motivator, aligning with Toubia and Stephen (2013) and Cheung and Lee (2012).

The study further reveals how factors like restaurant price, social network size and reputation status affect photo sharing, moderated by user experience. This reflects the strategic use of visuals to influence perceptions, as discussed by Invernizzi *et al.* (2022). Moreover, users with extensive social networks and elite status may leverage photo sharing to reinforce their influence and reputation within the online community. Sharing visually rich content of positive experiences helps them maintain their social standing and assert their taste and expertise. This behavior resonates with the findings of Atwal *et al.* (2018), where positive consumer experiences are more likely to be shared visually.

Finally, geographical distance also moderates these relationships, with distant users less likely to share photos related to an establishment's price, possibly due to diminished prestige over distance (Kim *et al.*, 2015). However, for users with vast social networks or elite status, distance enhances the likelihood of photo sharing, showcasing their broad experiences and bolstering their social capital. This reflects the idea that users with large social networks or high status often share travel photos, especially from distant places, to showcase their experiences and boost their social prestige (Gretzel and Yoo, 2008). The tendency to post more photos from afar may stem from a desire to share unique experiences, seen as more valuable due to the significant effort and resources involved in travel (Munar and Jacobsen, 2014).

5.2 Theoretical Implications

This study holds several theoretical implications, advancing the theoretical understanding of photo-posting behavior in online reviews. First, this study advances the understanding of photo-posting behavior in online reviews by examining the quantity of shared photos, a departure from the traditional binary focus on photo presence (Hu *et al.*, 2022; An *et al.*, 2020). We explore how factors like business price level, social network size and reputation status affect users' likelihood to share more photos, addressing a gap in visual eWOM research (Huang *et al.*, 2019; Zhang *et al.*, 2014). Using TAT, we investigate how specific task-level and social-level situational cues in online settings trigger photo-sharing behaviors, marking a significant expansion of TAT into digital consumer engagement. This approach offers fresh perspectives on the interplay between situational factors and user traits in online photo sharing, contributing to the broader discourse on consumer behavior in digital platforms.

Second, our use of TAT to examine mediating factors like conspicuous display, reputation seeking and need for social approval offers new insights into photo-sharing motivations. We expand the idea of conspicuous display beyond its traditional link to luxury travel (Hu *et al.*, 2022), showing it mediates the relationship between business price levels and photo sharing. This reveals how consumers use photos to showcase connections with high-end establishments, enriching our understanding of digital conspicuous consumption. Additionally, we explore how factors like social network size and reputation status act as novel trait activators in online settings, highlighting TAT's applicability to digital platforms. This sheds light on unique online behaviors and motivations, differentiating the drivers of visual from textual content sharing in online reviews and emphasizing the role of digital environments in enhancing user engagement with visual content.

Third, incorporating user experience and geographic distance as moderators adds depth to our study, examining how these factors influence the relationship between variables like establishment price, user reputation and social network size on photo-sharing. This approach reflects the context-specific nature of online behavior, as noted in recent studies (Lee and Kim, 2020), and provides insights for businesses aiming to boost online engagement. It also enhances the application of TAT by showcasing the interplay of situational cues, traits and context.

Furthermore, our multi-method approach, which combines user-generated data with experimental designs, represents a methodological leap forward. This strategy overcomes the limitations of survey-based or small-scale studies (Cho *et al.*, 2019; Malik *et al.*, 2016), offering a more thorough and dependable analysis. This fusion of real-world and experimental data provides a comprehensive view of online photo-sharing dynamics, reinforcing our findings' credibility and setting a precedent for future research in digital consumer behavior.

5.3 Practical Implications

This study provides practical insights for restaurant businesses and review platforms to encourage visual content sharing. We found that diners at high-priced establishments often post more photos to showcase their experiences, driven by conspicuous display. To capitalize on this, high-end restaurants can create a visually appealing presentation and ambiance that naturally encourage photo-taking. Additionally, engaging with customers' content by reposting their photos on the restaurant's official social media channels can also validate the customers' efforts and further encourage the sharing of visual content.

For users with elite status and wide social networks, businesses could implement tiered incentives, such as exclusive discounts or event invitations, to motivate photo sharing. Review platforms might highlight content from these influential users, offering them additional visibility. Businesses can consider launching online referral and brand ambassador programs targeting users with large networks to further leverage their influence, encouraging content sharing.

Considering user experience influences photo-sharing behavior, businesses should strive for exceptional service, as memorable experiences are more likely to be shared. Staff could assist in photo-taking, enhancing guests' likelihood to share their positive experiences online. The role of geographical distance suggests tailored marketing strategies; local events for nearby diners and highlighting unique aspects for distant visitors to promote photo sharing as part of their travel experience. For distant customers, emphasizing the dining experience's uniqueness, like cultural significance, can encourage sharing. Inviting users, especially those with extensive networks, to tag the restaurant in their photos can broaden the establishment's visibility. For elite users, exclusive experiences that affirm their status and personalized invitations to share their experiences can enrich the restaurant's narrative and attract more customers.

5.4 Limitations and Future Research

While this study offers valuable insights, it also highlights areas for future exploration. The use of cross-sectional data from Yelp.com limits our ability to confirm causality. Future research should use longitudinal data to better understand the causal relationships between user motivations, experiences and photo-sharing in reviews. Additionally, focusing on restaurant reviews on Yelp.com may not fully represent other industries or platforms. Expanding research to various sectors and review sites could broaden the understanding of the identified motivators and moderators. The study's geographic limitation to Las Vegas restaurants also suggests the need for research across diverse cultural settings to improve generalizability. Moreover, the lack of data from the post-COVID-19 era leaves a gap in understanding potential changes in online review behaviors. Future studies should investigate these aspects to provide insights into the evolving landscape of online consumer behavior.

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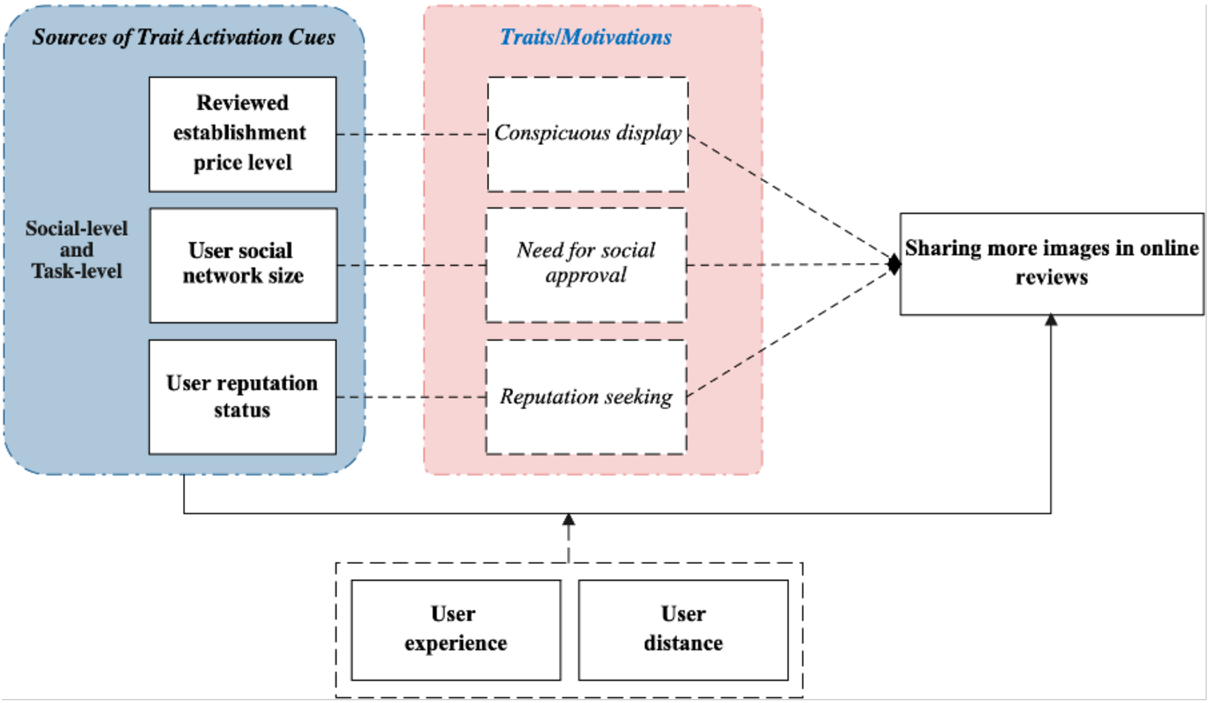

Figure 1. Research Framework
Source: Created by author

Table 1. Variable Measurement

Variable	Measurement	Mean	SD	Min	Max	Skewness	Kurtosis
Dependent Variable							
Number of photos in review *($RewPhotos_{ijk}$)*	Total number of photos in a specific review *i* for restaurant *j* posted by user *k*	0.837	2.033	0	50	4.437	46.72
Independent Variables							
Reviewed establishment price level ($ResPrice_j$)	Price level of restaurant *j*, ranging from $ (low-priced) to $$$$ (high-priced). Restaurant price levels are coded as 1 to 4 based on their $ to price level	2.322	0.752	1	4	0.585	3.123
User reputation status ($UserElite_{ik}$)	Binary variable indicating whether user *k* had earned an Elite badge at the time review *i* was posted (1 = yes; 0 = no)	-	-	0	1	1.447	3.095
User social network size ($UserFriends_k$)	The total number of friends for user *k*	7.189	39.19	0	5,818	26.26	1,786
Moderators							
User experience ($RewRating_{ijk}$)	Measured by the review *i*'s review rating for restaurant *j* given by user *k*; an integer measurement scale ranging from 1 (not good) to 5 (great)	4.009	1.245	1	5	-1.138	3.196
User distance ($UserDistance_{jk}$)	Measured by the distance between user *k*'s location and the review restaurant *j* location (in kilometer)	1094.663	1584.176	0.0265	15380.35	3.259	20.33
Control Variables							
Restaurant popularity	Number of reviews received by restaurant *j* before the focal review *i* (Zhang and Luo, 2023)	1440.571	1637.951	0	10621	2.233	9.034
Peer influence	Total number of reviews posted with photo(s) prior to the focal review *i* for the same restaurant *j* (Li, Zhang *et al*., 2023)	329.5	409.5	0	2649	2.339	9.254
User posted reviews	Number of reviews posted by the user *k* before the focal review *i* (Li *et al*., 2019)	1.781	6.006	0	118	9.560	137.3
User posted photos	Number of photos posted by the user *k* before the focal review *i* (Li *et al*., 2019)	3.445	28.66	0	1,468	24.20	796.3
Review length	Number of words in the focal review *i* (TextSTAT was used to calculate the length of the focal review) (An *et al*., 2020)	114.8	109.2	1	1,009	2.495	12.14
Review readability	Gunning–Fog Index (FOG; Gunning,1969) for the focal review text; the lower the grade, the better the readability (Li, Liu, *et al*., 2020 p. 6)	15.03	21.44	0.4	388.7	5.498	47.14
Review sentiment	Average sentiment score based on different aspects of the focal review text, calculated through aspect-based sentiment analysis (ABSA; Li, Ji, *et al*., 2022)	0.509	0.342	0	0.999	-0.0544	1.508
Year fixed effect	*n*−1 dummy variables, where *n* represents the year number; 16 dummies included as database covered from 2005 to 2021 (Hu *et al*., 2022)	-	-	-	-	-	-
Month fixed effect	*n*−1 dummy variables, where *n* represents the month number; 193 dummies included as database covered from 2005 to 2021 (Hu *et al*., 2022)	-	-	-	-	-	-

Source: Created by author

Table 2. Empirical Results—Influencing Factors and Number of Photos Posted Along with Reviews

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7	(8) model 8	(9) model 9	(10) model 10	(11) model 11	(12) model 12
ResPrice	**0.179*****	**0.230*****	**0.226*****							**0.192*****	**0.254*****	**0.248*****
	(36.63)	(49.63)	(41.01)							(41.91)	(55.43)	(45.74)
UserElite				**1.183*****	**0.409*****	**0.427*****				**0.840*****	**0.283*****	**0.289*****
				(166.33)	(46.42)	(30.68)				(101.16)	(31.24)	(20.29)
UserFriends							**0.241*****	**0.107*****	**0.115*****	**0.150*****	**0.093*****	**0.100*****
							(131.79)	(60.02)	(44.57)	(73.62)	(49.45)	(37.77)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Month fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
User fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
_cons	-0.618***	-3.158***	-3.069***	-0.576***	-2.697***	-2.608***	-1.117***	-2.941***	-2.844***	-1.494***	-3.027***	-2.906***
	(-51.57)	(-71.22)	(-51.25)	(-120.98)	(-60.80)	(-45.29)	(-130.68)	(-66.54)	(-47.88)	(-110.43)	(-68.64)	(-50.20)
Pseudo R2	0.0046	0.2072	0.2101	0.0771	0.2065	0.2103	0.0625	0.2096	0.2143	0.0994	0.2205	0.2248
ll (model)	-683092	-544080	-541961	-633366	-544548	-541884	-643389	-542404	-539137	-618045	-534915	-531913
N	401126	401126	400990	401126	401126	400990	401126	401126	400990	401126	401126	400990

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Table 3. Results for moderating role of user experience and user distance

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7
ResPrice	0.228***	0.223***	0.223***	0.288***	0.271***	0.271***	0.260***
	(39.92)	(61.16)	(47.64)	(18.45)	(25.43)	(16.44)	(16.10)
UserElite	0.995***	0.305***	0.305***	0.0589**	0.103***	0.103	0.0670
	(42.69)	(38.37)	(16.83)	(2.21)	(4.54)	(1.64)	(1.08)
UserFriends	0.120***	0.056***	0.056***	0.091***	0.037***	0.037***	0.034***
	(28.00)	(40.63)	(33.16)	(16.38)	(10.46)	(5.44)	(4.95)
RewRating	0.118***	0.129***	0.129***				0.128***
	(51.08)	(40.94)	(41.51)				(41.28)
ResPrice × RewRating	**0.063*****	**0.056*****	**0.056*****				**0.056*****
	(21.55)	(19.96)	(21.74)				(21.49)
UserElite × RewRating	**0.191*****	**0.154*****	**0.154*****				**0.156*****
	(16.84)	(22.21)	(16.03)				(16.31)
UserFriends × RewRating	**0.010*****	**0.010*****	**0.010*****				**0.010*****
	(9.00)	(9.56)	(10.96)				(11.45)
UserDistance				0.0376***	0.0473***	0.0473***	0.0450***
				(5.72)	(11.64)	(8.37)	(8.09)
ResPrice×UserDistance				**-0.007*****	**-0.009*****	**-0.009*****	**-0.008*****
				(-2.72)	(-5.15)	(-3.41)	(-3.19)
UserElite×UserDistance				**0.0363*****	**0.0311*****	**0.0311*****	**0.0331*****
				(8.65)	(8.80)	(3.41)	(3.67)
UserFriends×UserDistance				**0.003*****	**0.004*****	**0.004*****	**0.004*****
				(3.62)	(6.46)	(3.32)	(3.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
Month fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
User fixed effect	No	No	Yes	No	No	Yes	Yes
_cons	-0.774***	-1.435***	-1.435***	-3.430***	-1.404***	-1.404***	-1.601***
	(-38.27)	(-38.52)	(-25.93)	(-53.57)	(-32.20)	(-18.81)	(-21.55)
ll	-803593.0	-771332.9	-771332.9	-407025.0	-772896.8	-772896.8	-770926.8
N	401125	401125	401125	401126	401125	401125	401125

Source: Created by author

Appendix 1. Summary of Online Photo Sharing Literature

To curate Table A, we employed a systematic approach, selecting studies based on their relevance to photo-sharing behaviors. We focused on peer-reviewed empirical articles that specifically addressed online photo-sharing motivations, employing diverse theories and spanning various platforms to ensure a comprehensive perspective.

Table A. Summary of Online Photo Sharing Literature

Authors	Influencing factors/Motivations	Context	Sample	Method	Theory
Research method: Interviews					
Cho et al., 2019	Share memory, disseminate information, amusement (humor, fun), show off, appreciate beauty/cuteness, update status, share/evoke certain emotions, honor/celebrate, make an inquiry, self-presentation/self-expression, illustrate/Use as evidence, suggest/persuade, participate in an event, promote something, get confirmation, update profile, recall/remind, say hello	Online photo sharing	Undergraduate and graduate students	Inductive thematic analysis	Uses and gratification theory
Wang et al., 2017	Social and relational, self-image projection, emotion articulation, self-archiving, and information sharing	Traveler food photos	33 respondents from South Korea	Thematic analysis	Psychological ownership theory and functional theory
Oeldorf-Hirsch and Sundar, 2016	Seeking and showcasing experiences, technological affordances, social connection, and reaching out	Online photo sharing	460 students from large U.S. university	Focus groups and Factor analysis	Uses and gratifications theory
Research method: Survey					
Prado-Gascó et al., 2017	Information motivation, entertainment motivation, and fanship motivation	Social media	410 triathletes who attended a competition in Spain in 2015	fsQCA	Social exchange theory
Malik et al., 2016	Affection seeking, attention seeking, disclosure, entertainment, Habitual pastime, information sharing, social influence, social interaction	Facebook	368 respondents	Cross-sectional survey and EFA	Uses and gratifications theory
Lee et al., 2015	Social and psychological motives: social interaction, archiving, self-expression, escapism, and peeking	Instagram	212 Instagram users in Korea	PCA	-

Hunt et al., 2014	Technology diffusion factors: innovativeness and technology clusters, Impression management motives: self-expression and self-presentation	Photo-messaging behavior	682 undergraduate students at a Northeastern university	CFA and SEM	Technology acceptance model and diffusion theory
Stefanone et al., 2011	Self-worth, self-presentation, social support, network size	Facebook	311 university students	OLS regression	Self-worth theory of motivation
Nov et al., 2010	Intrinsic: enjoyment, commitment to the community Extrinsic: self-development, reputation building, tenure in community	Flickr	276 Flickr users	PCA and regression	Self-determination theory
Research method: Mixed methods					
Li, 2019	Gaining recognition and status, sharing tourism information, disclosure, and enjoyment	Sharing travel photos	18 participants who had experience in sharing travel photos in WeChat were interviewed; 486 participated in an online survey.	Content analysis, EFA, CFA, and K-means cluster analysis	-
Research method: Secondary big data					
An et al., 2020	Showcasing affordability for higher service level hotels, sharing positive experience, and complaining negative experiences in low-end hotels	Hotel review photos	538,000 reviews with 97,000 photos from New York City Hotels on TripAdvisor	LDA and multivariate linear regression analysis	Negativity bias theory
Hu et al., 2022	Traveler's status based on historical consumption and membership rank, the overall rating of reviews, and other controls like traveling with children and having a profile image	Online travel platform	Data from a leading provider of group tourism products in China, including over 1.2 million reviews covering over 70 thousand tourism products	Regression analysis	Self-enhancement theory
This study	Motivators: reviewed establishment price level, user reputation status, social network size Internal mechanisms: conspicuous display, seeking reputation, need for social approval Boundary conditions: user experience, user distance	Restaurant online review photos	401,126 reviews with 335,909 photos of restaurants in Las Vegas from Yelp; Online experiments with the participants from diverse cities in USA	PPML regression model using high-dimensional fixed effects; Hayes Process Model 4	TAT

Source: Created by author

Appendix 2. Control Variables and Descriptive Analysis

Control Variables

In consideration of potential confounders, we integrated control variables shown by previous studies to impact online review behavior. These encompass review-specific, user-specific, restaurant-specific, and time-specific variables. Initially, owing to the influence of their own or peer reviews on their review formation (Li *et al.*, 2019; Moe and Schweidel, 2012), we controlled for the user's previous review and photo-sharing behavior and peer influence. Subsequently, we adjusted for review characteristics like length, readability, and sentiment (Filieri *et al*., 2018, 2019; Li, Meng, et al., 2020; Li, Ji, et al., 2022). At the restaurant level, we controlled for restaurant popularity, as suggested by Filieri *et al*. (2018) and Zhang and Luo (2023), to account for its potential impact on photo sharing. In addition to the variables previously mentioned, we have incorporated "User_country_of_origin" as a control variable to account for cultural and geographical differences that may affect online review behavior. This variable was operationalized by classifying users based on the country information provided in their Yelp profiles, which allows us to consider the potential influence of international diversity on photo-sharing practices. By integrating "User_country_of_origin," we can refine our analysis to control for the nuanced effects of regional differences, as indicated by existing literature on the impact of cultural and geographical differences on online review behavior (Liang *et al*., 2022). Lastly, consistent with Hu *et al*. (2022), we included time-level fixed effects to capture yearly and monthly variations in photo-posting behavior. Incorporating these control variables into our regression models facilitates a more precise estimation of the relationships between the independent variables and the quantity of photos shared in reviews.

Descriptive Analysis

Our dataset for this research was procured from Yelp.com, a platform recognized as the premier restaurant review platform by Review Trackers (Zhang and Luo, 2023). This recognition has resulted in a surge of academic interest in the platform. Our sample comprises widely visited restaurants in Las Vegas, Nevada, USA, which offers a suitable context for this study due to its global reputation as a culinary and entertainment hub. Las Vegas was selected as the sample site for this study due to its unique characteristics in the restaurant industry. The city is known for its highly diversified restaurant scene, catering to a wide range of culinary tastes, from fast food to gourmet dining (Li, Ji *et al*., 2022). As a prominent global tourism hub, Las Vegas attracts a large number of international and domestic tourists annually (Tarlow and Santana, 2002), generating a substantial amount of user-generated content, including restaurant reviews. This vast trove of data provides a rich resource for academic research. Furthermore, the significance of the hospitality industry in Las Vegas' economy (Yang *et al*., 2012) underscores the practical implications of this research in both academic and industry contexts.

The city's diverse range of dining establishments, from high-end to casual eateries, attracts a multitude of visitors, making it an ideal setting for analyzing varied photo-sharing behaviors. We adopted a stratified sampling technique, considering various restaurant characteristics such as price range, whether the establishment is a chain or independent, and its operational status. The data, collected from January 2005 through February 2021, includes a broad array of factors: review content (e.g., review text, review images, review rating), restaurant details (e.g., price range, popularity, chain/independent status), and user profiles (e.g., annual elite status, friend count, user distance). The assembled dataset contains information from 300 restaurants, of which 114 are chain establishments. Cumulatively, these restaurants have amassed a total of 401,126 reviews from 232,848 unique users. Notably, 26.23% of these reviews (105,190) contained at least one photo. In total, the shared images in these reviews sum up to 335,909, resulting in an average of 0.84 photos per review.

We calculated the number of reviews and corresponding photos shared each year, as illustrated in Figure B1. The line graph reveals a persistent increment in the quantity of both reviews and photos published annually, indicating a surge in user engagement with review and photo-sharing activities on the platform. This escalating pattern over the years serves to underscore an emerging trend in the realm of user photo-sharing behavior. Each data point on the graph denotes a specific year, with the pinnacle of review and photo sharing activity observed in 2018. Figure B2 provides a glimpse into the yearly average number of photos included per review, derived from the dataset. The figure chronicles a steady augmentation in the quantity of photos embedded per review across the years.

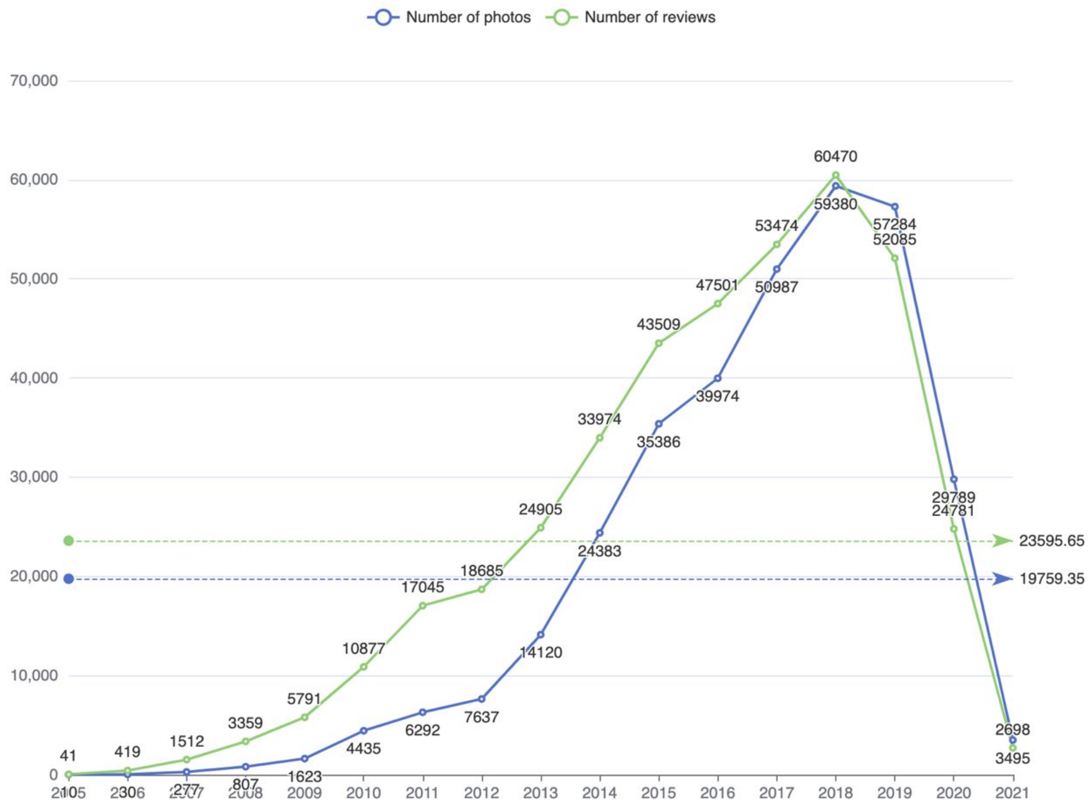

Figure B1. Annual Number of Reviews and Photos

Source: Created by author

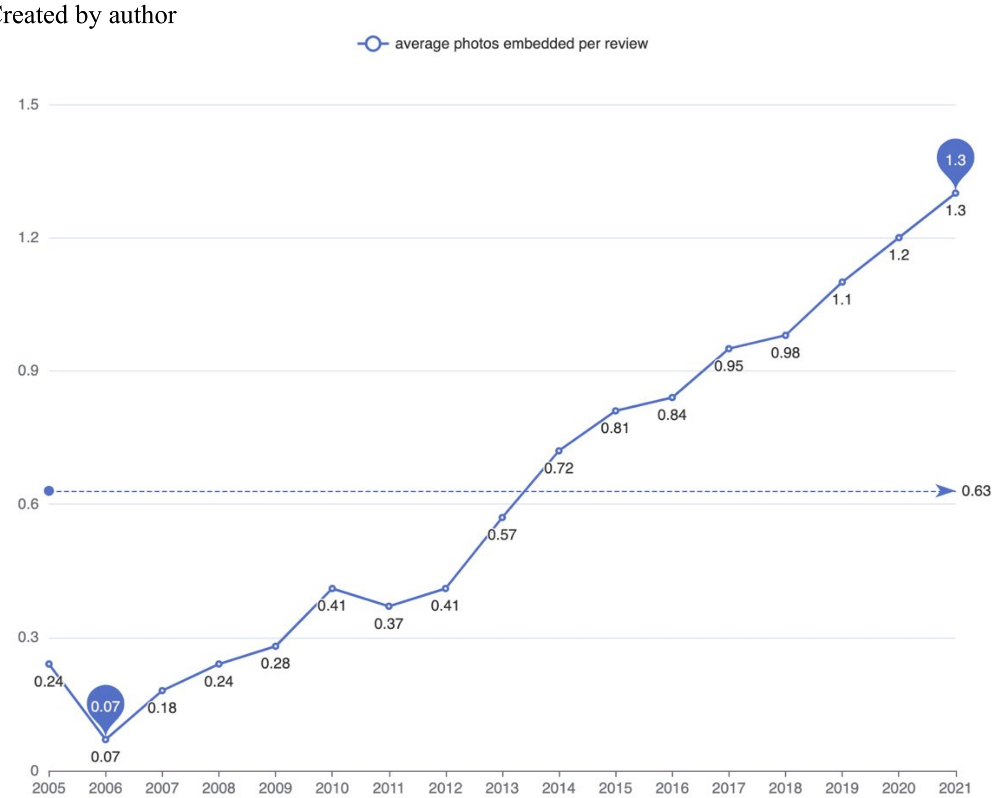

Figure B2. Yearly Average Photos Embedded Per Review

Source: Created by author

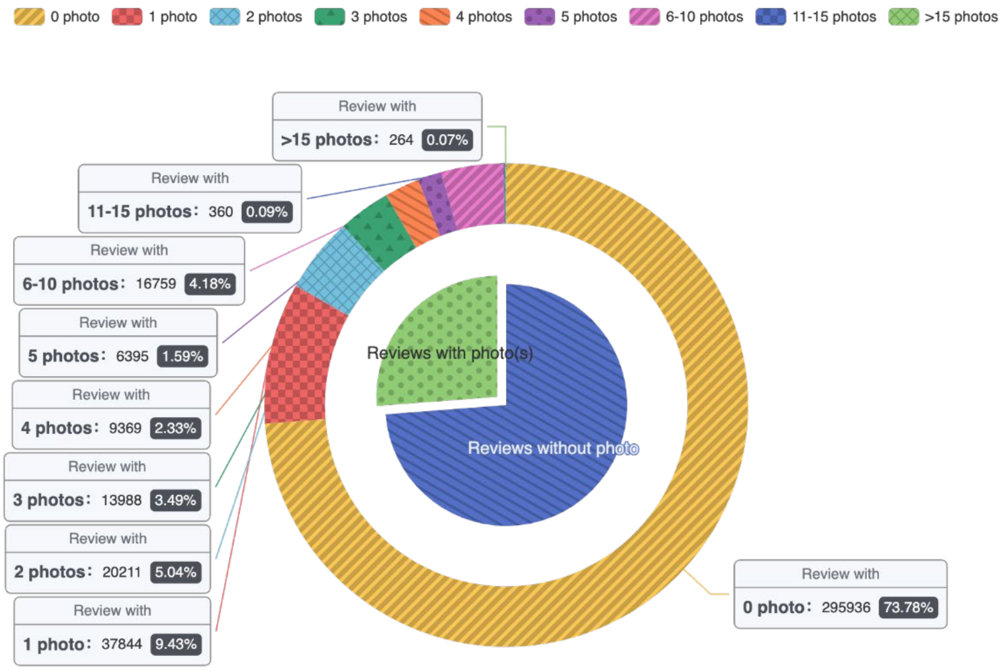

Figure B3. Distribution of Reviews Categorized by the Quantity of Review Photos
Source: Created by author

Figure B3 delineates the distribution of reviews, segmented according to varying quantities of review photos. Notwithstanding the evident upward trend in the number of photos incorporated per review, the overwhelming majority—over 70% of the reviews—are devoid of any photos. Among reviews that do incorporate pictures, close to 20% contain fewer than five pictures, nearly 5% encompass between 6 and 10 pictures, and a scant 2% include more than 10 pictures.

Table B. Descriptive Results of Dataset

Restaurant price (Number of restaurants)	Number of chain restaurants	Reviews posted with photo(s)	Total reviews received	Total photos embedded with reviews	Average photos per review
$ restaurant (30)	14 (46.67%)	9,496 (26.45%)	35,881	23,041	0.64
$$ restaurant (182)	83 (45.60%)	63,601 (27.14%)	234,230	184,869	0.79
$$$ restaurant (56)	12 (21.43%)	23,428 (24.23%)	97,114	87,711	0.90
$$$$ restaurant (32)	5 (15.63%)	8,665 (25.84%)	33,901	40,288	1.19
Total (300)	114	105,190	401,126	335,909	0.84

Source: Created by author

Table B provides a descriptive analysis of the dataset, which includes a range of restaurants classified by price levels, from the least expensive ($) to the most expensive ($$$$). These price levels are based on the number of dollar signs, a common way to denote price in many review platforms. In Yelp, "$" stands for consumption per capita under $10, "$$" for the range of $11–$30, "$$$" for $31–$60, and "$$$$" for over $61. In the dataset, 10% of restaurants were denoted by "$", 61% by "$$", 18.7% by "$$$", and approximately 11% by "$$$$". Roughly 25% of reviews at each price level contained photo(s).

The dataset analysis elucidates a direct correlation between restaurant price categories and the average number of photos shared per review. The least expensive restaurants, denoted by a single "$", have reviews that feature an average of 0.64 photos. A slight increment is noted in the “$$” category, where reviews contain, on average, 0.79 photos. A further increase can be observed in the “$$$” restaurant reviews, which feature an average of 0.90 photos per review. Most strikingly, the most upscale restaurants, signified by “$$$$”, have reviews that showcase the highest average number of photos at 1.19 per review. The average number of photos incorporated into restaurant reviews increases as the restaurant’s price level increases, indicating a relationship between consumer spending and photo sharing.

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Zhang, M. and Luo, L. (2023), “Can Consumer-Posted Photos Serve as a Leading Indicator of Restaurant Survival? Evidence from Yelp”, *Management Science*, Vol. 69 No. 1, pp. 25–50.

Appendix 3. Calculation of User Geographic Distance

The calculation of distance between a user's indicated location in their profile and a restaurant location suggested on its listing page involves employing a rigorous mathematical model to determine the spatial separation between their respective geographical coordinates. The calculation of user geographic distances, also known as Haversine distances, was accomplished using the distHaversine function from the geosphere package in R, as prescribed by Hijmans *et al*. (2017). The calculation accounts for the curvature of the Earth as well as the latitude and longitude values of the location of the user and the reviewed restaurant, generating an accurate and precise distance estimate. The specific calculation formula for the Haversine distance between user and reviewed establishment on the Earth's surface is as follows:

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_k) \times \cos(lat_j) \times \sin^2\left(\frac{\Delta lon}{2}\right)$$

$$c = 2 \times atan2\left(\sqrt{a}, \sqrt{1-a}\right)$$

$$d = R \times c$$

where

lat_k and lon_k represent the latitude and longitude of the user k,

lat_j and lon_j represent the latitude and longitude of the review restaurant j,

$\Delta lat = lat_j - lat_k$,

$\Delta lon = lon_j - lon_k$,

R denotes the mean radius of the Earth (e.g., 6,371 km),

a and c denote the calculation process and the order of operation, and

d signifies the distance between the two points.

Reference

Hijmans, R.J., Williams, E., Vennes, C. and Hijmans, M.R.J. (2017), "Package 'geosphere'", *Spherical trigonometry*, Vol. 1 No. 7, pp. 1–45.

Appendix 4. Detailed Results

Table 2, in Models 1–3, a positive and significant effect of restaurant price level (*ResPrice*) on the number of posted photos is evident (coefficients ranging from 0.179 to 0.230, $p < 0.0$), suggesting users are more likely to share more photos in high-priced restaurant reviews. User reputation status (*UserElite*) in Models 4–6 exhibits a similar pattern (coefficients ranging from 0.409 to 1.183, $p < 0.01$, $p < 0.0$), indicating elite users typically share more photos than their non-elite counterparts. Likewise, Models 7–9 reveal that users with large social networks (*UserFriends*) are prone to photo sharing (coefficients ranging from 0.107 to 0.241, $p < 0.0$), affirming H1, H2, and H3. Models 3, 6, and 9 also incorporate temporal controls, acknowledging potential seasonal fluctuations impacting photo posting volume. The user-level clustering accounts for potential correlations and heterogeneity among users, ensuring appropriately adjusted standard errors. This inclusion of fixed effects and clustering specifications addresses potential biases and confounding factors related to time-varying or user-specific characteristics, thereby bolstering the robustness and validity of our findings.

Table 3 delineates the results related to the moderating roles of user experience and distance on influential factors such as the reviewed establishment's price level and the user's social network size and reputation status, all in relation to the number of photos shared in online reviews. Models 3 and 6 incorporate fixed effects for the year and month and cluster standard errors at the user level to manage potential within-user correlation. Models 1–3 highlight significant positive moderating effects of user experience, as marked by review rating. In particular, when users have more satisfying experiences, the positive influence of the aforementioned factors on photo sharing strengthens. A rise in the number of photos posted corresponds with an increase in the reviewed establishment's price level (coefficient of $ResPrice \times RewRating = 0.063$, $p < 0.01$) and the user's social network size (coefficient of $UserFriends \times RewRating = 0.010$, $p < 0.01$), and reputation status (coefficient of $UserElite \times RewRating = 0.191$, $p < 0.01$). These results suggest that users satisfied with their experiences may be more motivated to seek reputation and social approval by posting more photos, thereby supporting H4a, 4b, and 4c.

In Models 4–6, user distance negatively moderates the relationship between the reviewed establishment's price level (coefficient of $ResPrice \times UserDistance = -0.007$, $p < 0.01$) and photo sharing. By contrast, it positively moderates the relationships between the user's social network size (coefficient of $UserFriends \times UserDistance = 0.003$, $p < 0.01$) and reputation status (coefficient of $UserElite \times UserDistance = 0.036$, $p < 0.01$) on consumer sharing more visual imagery contents in online reviews. The outcomes suggest that the impact of the establishment's price level on photo sharing lessens as users are farther from the restaurant, whereas the effect of user reputation status and social network size strengthens. Consequently, H5a is rejected, whereas H5b and 5c are supported.

Table 2. Empirical Results—Influencing Factors and Number of Photos Posted Along with Reviews

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11	model 12
ResPrice	**0.179*****	**0.230*****	**0.226*****							**0.192*****	**0.254*****	**0.248*****
	(36.63)	(49.63)	(41.01)							(41.91)	(55.43)	(45.74)
UserElite				**1.183*****	**0.409*****	**0.427*****				**0.840*****	**0.283*****	**0.289*****
				(166.33)	(46.42)	(30.68)				(101.16)	(31.24)	(20.29)
UserFriends							**0.241*****	**0.107*****	**0.115*****	**0.150*****	**0.093*****	**0.100*****
							(131.79)	(60.02)	(44.57)	(73.62)	(49.45)	(37.77)
Restaurant popularity		-0.560***	-0.476***		-0.486***	-0.380***		-0.503***	-0.369***		-0.586***	-0.475***
		(-72.74)	(-46.70)		(-66.54)	(-37.68)		(-69.73)	(-38.08)		(-77.05)	(-45.41)
User_posted_reviews		-0.071***	-0.068***		-0.100***	-0.097***		-0.117***	-0.113***		-0.117***	-0.115***
		(-15.74)	(-6.93)		(-22.80)	(-9.73)		(-26.67)	(-11.61)		(-26.72)	(-11.48)
User_posted _photos		0.431***	0.419***		0.386***	0.370***		0.386***	0.365***		0.366***	0.347***
		(137.02)	(57.90)		(120.07)	(52.69)		(122.33)	(52.10)		(113.78)	(48.13)
User_country_of_origin		-0.005***	-0.006***		-0.005***	-0.005***		-0.007***	-0.007***		-0.006***	-0.006***
		(-10.38)	(-8.39)		(-9.63)	(-7.50)		(-13.24)	(-10.55)		(-11.09)	(-8.72)
Review_length		0.566***	0.577***		0.538***	0.548***		0.548***	0.561***		0.466***	0.476***
		(110.55)	(77.10)		(101.92)	(73.15)		(107.30)	(75.32)		(88.51)	(64.63)
Review_readbility		-0.121***	-0.107***		-0.100***	-0.083***		-0.104***	-0.085***		-0.115***	-0.096***
		(-22.30)	(-8.95)		(-18.89)	(-8.74)		(-19.43)	(-7.81)		(-21.55)	(-9.92)
Review_sentiment		0.669***	0.659***		0.684***	0.672***		0.673***	0.656***		0.636***	0.619***
		(63.54)	(52.12)		(64.90)	(52.43)		(63.61)	(51.67)		(60.54)	(48.80)
Peer_influence		0.685***	0.552***		0.600***	0.436***		0.631***	0.427***		0.704***	0.528***
		(87.49)	(49.73)		(79.99)	(39.54)		(84.90)	(39.95)		(91.70)	(46.56)
Year fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Month fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
User fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
_cons	-0.618***	-3.158***	-3.069***	-0.576***	-2.697***	-2.608***	-1.117***	-2.941***	-2.844***	-1.494***	-3.027***	-2.906***
	(-51.57)	(-71.22)	(-51.25)	(-120.98)	(-60.80)	(-45.29)	(-130.68)	(-66.54)	(-47.88)	(-110.43)	(-68.64)	(-50.20)
Pseudo R2	0.0046	0.2072	0.2101	0.0771	0.2065	0.2103	0.0625	0.2096	0.2143	0.0994	0.2205	0.2248
ll (model)	-683092	-544080	-541961	-633366	-544548	-541884	-643389	-542404	-539137	-618045	-534915	-531913
N	401126	401126	400990	401126	401126	400990	401126	401126	400990	401126	401126	400990

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Table 3. Results for moderating role of user experience and user distance

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7
ResPrice	0.228***	0.223***	0.223***	0.288***	0.271***	0.271***	0.260***
	(39.92)	(61.16)	(47.64)	(18.45)	(25.43)	(16.44)	(16.10)
UserElite	0.995***	0.305***	0.305***	0.0589**	0.103***	0.103	0.0670
	(42.69)	(38.37)	(16.83)	(2.21)	(4.54)	(1.64)	(1.08)
UserFriends	0.120***	0.056***	0.056***	0.091***	0.037***	0.037***	0.034***
	(28.00)	(40.63)	(33.16)	(16.38)	(10.46)	(5.44)	(4.95)
RewRating	0.118***	0.129***	0.129***				0.128***
	(51.08)	(40.94)	(41.51)				(41.28)
ResPrice × RewRating	**0.063*****	**0.056*****	**0.056*****				**0.056*****
	(21.55)	(19.96)	(21.74)				(21.49)
UserElite × RewRating	**0.191*****	**0.154*****	**0.154*****				**0.156*****
	(16.84)	(22.21)	(16.03)				(16.31)
UserFriends × RewRating	**0.010*****	**0.010*****	**0.010*****				**0.010*****
	(9.00)	(9.56)	(10.96)				(11.45)
UserDistance				0.0376***	0.0473***	0.0473***	0.0450***
				(5.72)	(11.64)	(8.37)	(8.09)
ResPrice×UserDistance				**-0.007*****	**-0.009*****	**-0.009*****	**-0.008*****
				(-2.72)	(-5.15)	(-3.41)	(-3.19)
UserElite×UserDistance				**0.0363*****	**0.0311*****	**0.0311*****	**0.0331*****
				(8.65)	(8.80)	(3.41)	(3.67)
UserFriends×UserDistance				**0.003*****	**0.004*****	**0.004*****	**0.004*****
				(3.62)	(6.46)	(3.32)	(3.26)
Restaurant popularity		-0.326***	-0.326***	-0.736***	-0.361***	-0.361***	-0.337***
		(-49.32)	(-43.19)	(-80.13)	(-54.37)	(-46.76)	(-44.16)
User_posted_reviews		-0.144***	-0.144***	-0.0679***	-0.119***	-0.119***	-0.118***
		(-35.21)	(-14.19)	(-10.97)	(-28.36)	(-11.35)	(-11.26)
User_posted _photos		0.788***	0.788***	0.470***	0.807***	0.807***	0.806***
		(213.08)	(47.88)	(111.20)	(211.31)	(49.73)	(49.57)
User_country_of_origin		-0.005***	-0.005***	-0.005***	-0.003***	-0.003***	-0.003***
		(-9.91)	(-6.63)	(-7.58)	(-6.54)	(-4.38)	(-4.44)
Review_length		0.360***	0.360***	0.513***	0.383***	0.383***	0.362***
		(88.96)	(63.12)	(82.94)	(94.80)	(67.41)	(64.11)
Review_readbility		-0.078***	-0.078***	-0.168***	-0.083***	-0.083***	-0.083***
		(-17.52)	(-7.04)	(-24.48)	(-18.44)	(-7.49)	(-7.43)
Review_sentiment		0.147***	0.147***	0.808***	0.522***	0.522***	0.153***
		(12.93)	(10.84)	(61.43)	(61.37)	(56.10)	(11.27)
Peer_influence		0.341***	0.341***	0.859***	0.369***	0.369***	0.338***
		(46.67)	(44.72)	(92.92)	(50.36)	(47.76)	(44.32)
Year fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
Month fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
User fixed effect	No	No	Yes	No	No	Yes	Yes
_cons	-0.774***	-1.435***	-1.435***	-3.430***	-1.404***	-1.404***	-1.601***
	(-38.27)	(-38.52)	(-25.93)	(-53.57)	(-32.20)	(-18.81)	(-21.55)
ll	-803593.0	-771332.9	-771332.9	-407025.0	-772896.8	-772896.8	-770926.8
N	401125	401125	401125	401126	401125	401125	401125

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Appendix 5. Robustness Check Using Alternative Measurement

To bolster the robustness of our primary empirical findings, we performed two additional analyses. First, we adopted an alternative metric for dependent variable by replacing the number of photos in reviews with a natural logarithmic transformation variable Log (*Review photos*+1). This transformation facilitated a different perspective on the presence or absence of photos in reviews, allowing us to examine the factors influencing the likelihood of including photos in a review rather than the quantity of photos. This aligns with the approach suggested by Greene (2012), who highlights the importance of examining the consistency of results across varying model specifications.

Second, given that our dataset spans the COVID-19 pandemic period, we aimed to account for potential shifts in user behavior during this time. According to Bikhchandani and Sharma (2021), consumer behavior during crises can significantly deviate from standard patterns, making it imperative to check if our findings hold in non-crisis periods. As such, we performed a supplementary analysis confined to pre-pandemic data, collected before January 2020. These robustness check enhance the robustness of our findings by mitigating potential concerns the potential impact of the COVID-19 pandemic on user behavior. The results are presented in Tables E1- E4, which indicate a high degree of consistency with the findings from the primary models. The outcomes align closely with our primary models' results (Tables 2 and 3). This cross-analysis consistency lends further credibility and generalizability to our empirical findings.

Table E1. Robustness results_Log(Review photos+1)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10	(11) Model 11	(12) Model 12
ResPrice	**0.0249*****	**0.0496*****	**0.0482*****							**0.0293*****	**0.0563*****	**0.0549*****
	(19.10)	(41.68)	(35.03)							(23.57)	(47.65)	(39.82)
UserElite				**0.425*****	**0.161*****	**0.167*****				**0.339*****	**0.125*****	**0.129*****
				(182.40)	(66.05)	(37.45)				(130.79)	(48.69)	(28.09)
UserFriends							**0.0614*****	**0.0275*****	**0.0294*****	**0.0338*****	**0.0218*****	**0.0233*****
							(144.51)	(65.90)	(55.86)	(72.44)	(49.45)	(43.44)
Restaurant popularity		-0.145***	-0.126***		-0.134***	-0.110***		-0.137***	-0.106***		-0.156***	-0.128***
		(-80.79)	(-54.56)		(-76.53)	(-48.58)		(-78.07)	(-47.17)		(-87.57)	(-55.39)
User_posted_reviews		-0.029***	-0.026***		-0.045***	-0.042***		-0.047***	-0.044***		-0.052***	-0.050***
		(-22.11)	(-10.47)		(-33.74)	(-15.73)		(-35.56)	(-17.18)		(-39.06)	(-18.41)
User_posted _photos		0.267***	0.264***		0.248***	0.244***		0.255***	0.250***		0.244***	0.239***
		(229.00)	(92.22)		(207.84)	(76.38)		(217.21)	(85.56)		(205.10)	(75.49)
User_country_of_origin		-0.002***	-0.002***		-0.001***	-0.001***		-0.002***	-0.002***		-0.002***	-0.002***
		(-10.52)	(-7.62)		(-9.20)	(-6.56)		(-12.65)	(-9.13)		(-10.21)	(-7.34)
Review_length		0.154***	0.156***		0.140***	0.141***		0.146***	0.148***		0.126***	0.128***
		(120.84)	(89.05)		(107.64)	(81.89)		(114.13)	(85.13)		(96.87)	(74.83)
Review_readbility		-0.045***	-0.042***		-0.043***	-0.039***		-0.040***	-0.035***		-0.045***	-0.040***
		(-30.81)	(-17.92)		(-29.95)	(-15.68)		(-27.73)	(-14.87)		(-31.19)	(-15.97)
Review_sentiment		0.197***	0.196***		0.194***	0.193***		0.191***	0.188***		0.187***	0.184***
		(71.08)	(68.12)		(70.27)	(66.74)		(68.99)	(65.44)		(67.79)	(64.11)
Peer_influence		0.175***	0.146***		0.161***	0.125***		0.168***	0.122***		0.184***	0.142***
		(102.29)	(60.06)		(96.56)	(52.41)		(100.72)	(51.58)		(108.43)	(58.53)
Year fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Month fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Cluster(user_id)	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
_cons	0.273***	-0.367***	-0.355***	0.243***	-0.223***	-0.212***	0.130***	-0.305***	-0.297***	0.0818***	-0.311***	-0.297***
	(85.71)	(-31.14)	(-22.65)	(229.16)	(-19.01)	(-13.49)	(77.43)	(-26.14)	(-19.01)	(24.34)	(-26.50)	(-18.71)
R^2	0.001	0.234	0.236	0.077	0.239	0.242	0.049	0.239	0.242	0.090	0.247	0.251
adj. R^2	0.001	0.234	0.236	0.077	0.239	0.241	0.049	0.239	0.242	0.090	0.247	0.250
F	364.7	13596.8	3097.9	33271.1	13975.8	2984.0	20882.4	13973.0	3210.5	13157.9	11971.2	2655.0
N	401126	401126	401125	401126	401126	401125	401126	401126	401125	401126	401126	401125

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Table E2. Robustness results_Log(Review photos+1)——moderators

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7
ResPrice	0.0543^{***}	0.0529^{***}	0.0529^{***}	0.0707^{***}	0.0698^{***}	0.0698^{***}	0.0667^{***}
	(46.14)	(44.84)	(39.02)	(20.47)	(20.25)	(16.39)	(15.90)
UserElite	0.117^{***}	0.120^{***}	0.120^{***}	0.0325^{***}	0.0390^{***}	0.0390^{**}	0.0273^{*}
	(45.60)	(46.81)	(26.50)	(4.42)	(5.30)	(2.36)	(1.68)
UserFriends	0.0202^{***}	0.0218^{***}	0.0218^{***}	0.0140^{***}	0.0153^{***}	0.0153^{***}	0.0140^{***}
	(46.00)	(49.39)	(40.92)	(12.15)	(13.35)	(9.28)	(8.52)
RewRating	0.0483^{***}	0.0504^{***}	0.0504^{***}				0.0501^{***}
	(47.41)	(49.41)	(50.29)				(50.06)
ResPrice × RewRating	$\mathbf{0.0168}^{***}$	$\mathbf{0.0161}^{***}$	$\mathbf{0.0161}^{***}$				$\mathbf{0.0159}^{***}$
	(18.40)	(17.70)	(19.95)				(19.63)
UserElite × RewRating	$\mathbf{0.0374}^{***}$	$\mathbf{0.0363}^{***}$	$\mathbf{0.0363}^{***}$				$\mathbf{0.0369}^{***}$
	(16.66)	(16.19)	(12.86)				(13.16)
UserFriends × RewRating	$\mathbf{0.00260}^{***}$	$\mathbf{0.00250}^{***}$	$\mathbf{0.00250}^{***}$				$\mathbf{0.00267}^{***}$
	(7.81)	(7.52)	(8.57)				(9.18)
UserDistance				0.0160^{***}	0.0186^{***}	0.0186^{***}	0.0178^{***}
				(12.20)	(14.14)	(12.19)	(11.84)
ResPrice×UserDistance				$\mathbf{-0.0031}^{***}$	$\mathbf{-0.0033}^{***}$	$\mathbf{-0.0033}^{***}$	$\mathbf{-0.0031}^{***}$
				(-5.53)	(-5.92)	(-4.83)	(-4.60)
UserElite×UserDistance				$\mathbf{0.0131}^{***}$	$\mathbf{0.0123}^{***}$	$\mathbf{0.0123}^{***}$	$\mathbf{0.0129}^{***}$
				(11.45)	(10.78)	(4.97)	(5.26)
UserFriends×UserDistance				$\mathbf{0.00131}^{***}$	$\mathbf{0.00137}^{***}$	$\mathbf{0.00137}^{***}$	$\mathbf{0.00135}^{***}$
				(6.81)	(7.16)	(4.94)	(4.87)
Restaurant popularity	-0.150^{***}	-0.119^{***}	-0.119^{***}	-0.163^{***}	-0.132^{***}	-0.132^{***}	-0.124^{***}
	(-84.85)	(-55.83)	(-52.02)	(-90.53)	(-61.72)	(-56.58)	(-53.25)
User_posted_reviews	-0.0515^{***}	-0.0495^{***}	-0.0495^{***}	-0.0427^{***}	-0.0394^{***}	-0.0394^{***}	-0.0392^{***}
	(-39.05)	(-37.52)	(-18.45)	(-31.48)	(-28.98)	(-14.01)	(-14.05)
User_posted _photos	0.244^{***}	0.238^{***}	0.238^{***}	0.251^{***}	0.246^{***}	0.246^{***}	0.245^{***}
	(205.99)	(199.30)	(75.34)	(205.15)	(198.97)	(77.06)	(77.13)
User_country_of_origin	-0.0015^{***}	-0.0016^{***}	-0.0016^{***}	-0.0010^{***}	-0.0010^{***}	-0.0010^{***}	-0.0010^{***}
	(-10.30)	(-10.75)	(-7.35)	(-6.63)	(-6.59)	(-4.51)	(-4.56)
Review_length	0.119^{***}	0.121^{***}	0.121^{***}	0.127^{***}	0.129^{***}	0.129^{***}	0.122^{***}
	(91.29)	(92.57)	(70.96)	(97.44)	(98.89)	(76.37)	(72.45)
Review_readbility	-0.0454^{***}	-0.0397^{***}	-0.0397^{***}	-0.0470^{***}	-0.0414^{***}	-0.0414^{***}	-0.0414^{***}
	(-31.72)	(-27.51)	(-15.96)	(-32.65)	(-28.60)	(-16.66)	(-16.65)
Review_sentiment	0.0528^{***}	0.0450^{***}	0.0450^{***}	0.189^{***}	0.186^{***}	0.186^{***}	0.0475^{***}
	(14.40)	(12.26)	(10.84)	(68.51)	(67.61)	(64.64)	(11.41)
Peer_influence	0.178^{***}	0.130^{***}	0.130^{***}	0.188^{***}	0.140^{***}	0.140^{***}	0.129^{***}
	(105.07)	(55.16)	(54.28)	(110.40)	(59.34)	(58.02)	(53.79)
Year fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
Month fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
Cluster(user_id)	No	No	Yes	No	No	Yes	Yes
_cons	-0.396^{***}	-0.387^{***}	-0.387^{***}	-0.374^{***}	-0.369^{***}	-0.369^{***}	-0.455^{***}
	(-33.07)	(-32.13)	(-24.22)	(-26.62)	(-26.20)	(-19.41)	(-23.96)
R^2	0.255	0.258	0.258	0.249	0.253	0.253	0.261
adj. R^2	0.255	0.258	0.258	0.249	0.252	0.252	0.260
F	9141.9	8417.1	2349.2	8867.3	8153.0	2011.3	1916.5
N	401126	401125	401125	401126	401125	401125	401125

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Table E3. Robustness Results (Before COVID-19 Pandemic)

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7	(8) model 8	(9) model 9	(10) model 10	(11) model 11	(12) model 12
ResPrice	**0.165*****	**0.225*****	**0.221*****							**0.181*****	**0.250*****	**0.244*****
	(31.81)	(45.73)	(38.16)							(37.27)	(51.19)	(42.47)
UserElite				**1.175*****	**0.395*****	**0.414*****				**0.811*****	**0.257*****	**0.263*****
				(155.97)	(42.20)	(27.76)				(92.74)	(26.74)	(17.47)
UserFriends							**0.248*****	**0.111*****	**0.119*****	**0.159*****	**0.0986*****	**0.105*****
							(126.56)	(58.02)	(43.01)	(73.24)	(48.82)	(37.30)
Restaurant popularity		-0.552***	-0.465***		-0.479***	-0.369***		-0.496***	-0.358***		-0.578***	-0.463***
		(-69.84)	(-44.50)		(-64.00)	(-35.95)		(-67.24)	(-36.19)		(-74.10)	(-43.32)
User_posted_reviews		0.567***	0.579***		0.542***	0.552***		0.546***	0.559***		0.468***	0.479***
		(104.39)	(72.77)		(96.78)	(69.49)		(100.74)	(70.57)		(84.03)	(61.20)
User_posted _photos		-0.122***	-0.107***		-0.102***	-0.0844***		-0.104***	-0.0841***		-0.117***	-0.0966***
		(-21.60)	(-9.21)		(-18.48)	(-8.50)		(-18.73)	(-7.81)		(-20.96)	(-9.53)
User_country_of_origin		0.668***	0.659***		0.685***	0.674***		0.673***	0.656***		0.637***	0.620***
		(59.91)	(49.35)		(61.36)	(50.22)		(60.08)	(49.22)		(57.18)	(46.48)
Review_length		0.675***	0.539***		0.589***	0.424***		0.620***	0.414***		0.695***	0.515***
		(83.18)	(47.03)		(76.11)	(37.50)		(80.85)	(37.57)		(87.31)	(44.17)
Review_readbility		-0.0639***	-0.0615***		-0.0928***	-0.0910***		-0.111***	-0.109***		-0.111***	-0.110***
		(-13.62)	(-5.90)		(-20.39)	(-8.59)		(-24.47)	(-10.52)		(-24.42)	(-10.31)
Review_sentiment		0.434***	0.422***		0.390***	0.375***		0.387***	0.366***		0.370***	0.351***
		(130.70)	(54.83)		(114.75)	(49.46)		(116.28)	(49.17)		(108.73)	(45.07)
Peer_influence		-0.00548***	-0.00550***		-0.00517***	-0.00512***		-0.00716***	-0.00731***		-0.00599***	-0.00608***
		(-10.03)	(-7.98)		(-9.35)	(-7.14)		(-12.98)	(-10.15)		(-10.93)	(-8.45)
Year fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Month fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
User fixed effect	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
_cons	-0.614***	-3.167***	-3.099***	-0.603***	-2.715***	-2.654***	-1.187***	-2.947***	-2.886***	-1.531***	-3.050***	-2.956***
	(-48.53)	(-68.46)	(-50.81)	(-119.97)	(-58.66)	(-44.34)	(-128.30)	(-63.98)	(-47.17)	(-105.63)	(-66.30)	(-49.19)
ll (model)	-627045	-499713	-497683	-582390	-500222	-497711	-588958	-497658	-494560	-567774	-491373	-488512
N	373647	373647	373511	373647	373647	373511	373647	373647	373511	373647	373647	373511

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Table E4. Robustness Results (Before COVID-19 Pandemic)——moderators

	(1) model 1	(2) model 2	(3) model 3	(4) model 4	(5) model 5	(6) model 6	(7) model 7
ResPrice	0.214***	0.210***	0.210***	0.277***	0.277***	0.254***	0.244***
	(57.25)	(56.24)	(43.89)	(16.66)	(16.67)	(15.03)	(14.68)
UserElite	0.271***	0.278***	0.278***	0.0312	0.0613**	0.0710	0.0416
	(33.29)	(34.07)	(15.50)	(1.09)	(2.15)	(1.12)	(0.66)
UserFriends	0.0524***	0.0568***	0.0568***	0.0945***	0.0988***	0.0369***	0.0335***
	(37.32)	(40.21)	(32.99)	(15.81)	(16.66)	(5.32)	(4.83)
RewRating	0.120***	0.126***	0.126***				0.125***
	(37.19)	(38.79)	(39.34)				(39.19)
ResPrice × RewRating	**0.0540*** **	**0.0523*** **	**0.0523*** **				**0.0514*** **
	(18.49)	(17.90)	(19.50)				(19.22)
UserElite × RewRating	**0.154*** **	**0.152*** **	**0.152*** **				**0.153*** **
	(21.55)	(21.28)	(15.54)				(15.74)
UserFriends × RewRating	**0.0104*** **	**0.0101*** **	**0.0101*** **				**0.0106*** **
	(9.73)	(9.47)	(10.68)				(11.19)
UserDistance				0.0340***	0.0447***	0.0446***	0.0427***
				(4.86)	(6.42)	(7.67)	(7.44)
ResPrice×UserDistance				**-0.0058** **	**-0.0076*** **	**-0.0080*** **	**-0.0074*** **
				(-2.20)	(-2.87)	(-3.02)	(-2.83)
UserElite×UserDistance				**0.0370*** **	**0.0316*** **	**0.0311*** **	**0.0328*** **
				(8.27)	(7.09)	(3.34)	(3.56)
UserFriends×UserDistance				**0.00361*** **	**0.00447*** **	**0.00408*** **	**0.00402*** **
				(3.71)	(4.63)	(3.49)	(3.43)
Restaurant popularity	-0.394***	-0.312***	-0.312***	-0.733***	-0.563***	-0.346***	-0.322***
	(-71.53)	(-46.68)	(-41.04)	(-77.46)	(-51.34)	(-44.56)	(-42.04)
User_posted_reviews	-0.139***	-0.134***	-0.134***	-0.0630***	-0.0490***	-0.110***	-0.109***
	(-33.64)	(-32.48)	(-13.30)	(-9.77)	(-7.59)	(-10.44)	(-10.36)
User_posted _photos	0.805***	0.789***	0.789***	0.478***	0.458***	0.808***	0.807***
	(212.50)	(206.66)	(46.62)	(107.17)	(101.44)	(48.44)	(48.26)
User_country_of_origin	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.003***	-0.003***
	(-9.48)	(-9.62)	(-6.39)	(-7.78)	(-7.22)	(-4.24)	(-4.30)
Review_length	0.346***	0.351***	0.351***	0.514***	0.526***	0.375***	0.353***
	(83.69)	(84.76)	(60.20)	(78.41)	(79.77)	(64.45)	(61.22)
Review_readbility	-0.092***	-0.077***	-0.077***	-0.173***	-0.139***	-0.081***	-0.081***
	(-20.48)	(-16.90)	(-6.91)	(-24.04)	(-19.25)	(-7.34)	(-7.28)
Review_sentiment	0.165***	0.144***	0.144***	0.808***	0.790***	0.508***	0.150***
	(14.18)	(12.39)	(10.38)	(57.91)	(56.89)	(53.10)	(10.77)
Peer_influence	0.449***	0.323***	0.323***	0.851***	0.600***	0.351***	0.321***
	(84.66)	(43.65)	(41.97)	(88.71)	(48.52)	(45.04)	(41.70)
Year fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
Month fixed effect	No	Yes	Yes	No	Yes	Yes	Yes
User fixed effect	No	No	Yes	No	No	Yes	Yes
_cons	-1.392***	-1.385***	-1.385***	-3.387***	-26.30	-1.345***	-1.537***
	(-37.12)	(-36.74)	(-24.97)	(-50.37)	(-0.00)	(-17.83)	(-20.49)
ll	-715893	-715242	-715242	-371088	-369870	-716652	-714870
N	373647	373646	373646	373647	373647	373646	373646

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors are clustered at the user level and reported in parentheses.

Source: Created by author

Appendix 6. Supplementary Materials for Experiments

Experiment 1

Pretest Participants and Procedure

A pretest was designed to evaluate the effectiveness of manipulating restaurant price levels (budget, mid-range, high-end) for Experiment 1. We developed three scenarios, each representing a different price level. Participants first engaged with a scenario where they read the lead-in based on the assigned scenario "*Imagine you recently visited a budget-friendly/mid-range/high-end restaurant and had an experience you wish to share. Picture the ambiance, the quality of food, and the overall service. Now, as you prepare to write an online review*." Then, participants were shown a Yelp page mock-up representing a restaurant at a specific price level, indicated by $, $$, or $$$ symbols for budget, mid-range, and high-end categories, respectively. Participants (N = 60, M_{age} = 33.6, 55% male), randomly divided into three groups, were USA residents from Amazon's Mechanical Turk (Mturk). Each group was presented with a description of a fictional restaurant corresponding to one of the price levels. They were then required to complete manipulation checks assessing their perception of the restaurant's price level using a 7-point Likert scale from '1 - very affordable' to '7 = very expensive', and "*To what extent do you think the price of the restaurant in the situation is budget-friendly/mid-range/high-end* (1 = Strongly disagree, 7 = Strongly agree). While both questions were included in the main experiment 1, only the first question was used as the primary measure for the manipulation check. This decision was based on the directness and simplicity of the first question in capturing the participants' immediate perception of price level, which is crucial for validating the effectiveness of our price level manipulation. The second question, although valuable for providing additional insights into participants' nuanced understanding of price categories, was considered supplementary and not the central criterion for the manipulation check.

Pretest Results

Perceived price levels across scenarios were consistent with manipulations, reflected in overall mean (M = 5.88) surpassing 5.5 on a 7-point scale, indicating alignment with assigned price categories: budget-friendly (M_{budget} = 6.10), mid-range ($M_{mid\text{-}range}$ = 5.85), and high-end ($M_{high=end}$ = 5.70). This confirms the effectiveness of our scenario manipulations in conveying the intended price perceptions.

We further conducted a one-way ANOVA to compare the perception of the restaurant's price level across the three groups ('1 - very affordable' to '7 = very expensive'). The analysis revealed significant differences (F (2, 57) = 45.826, p < 0.01), indicating that participants effectively distinguished between the budget, mid-range, and high-end restaurant scenarios (see Figure F1 for experiment stimuli). Specifically, the high-end group rated the restaurant as significantly more expensive ($M_{high\text{-}end}$ = 6.0) compared to the budget (M_{budget} = 3.40) and mid-range groups ($M_{mid\text{-}range}$ = 5.25). This confirmed that participants could effectively distinguish between different restaurant price levels, validating the manipulation for the main experiment.

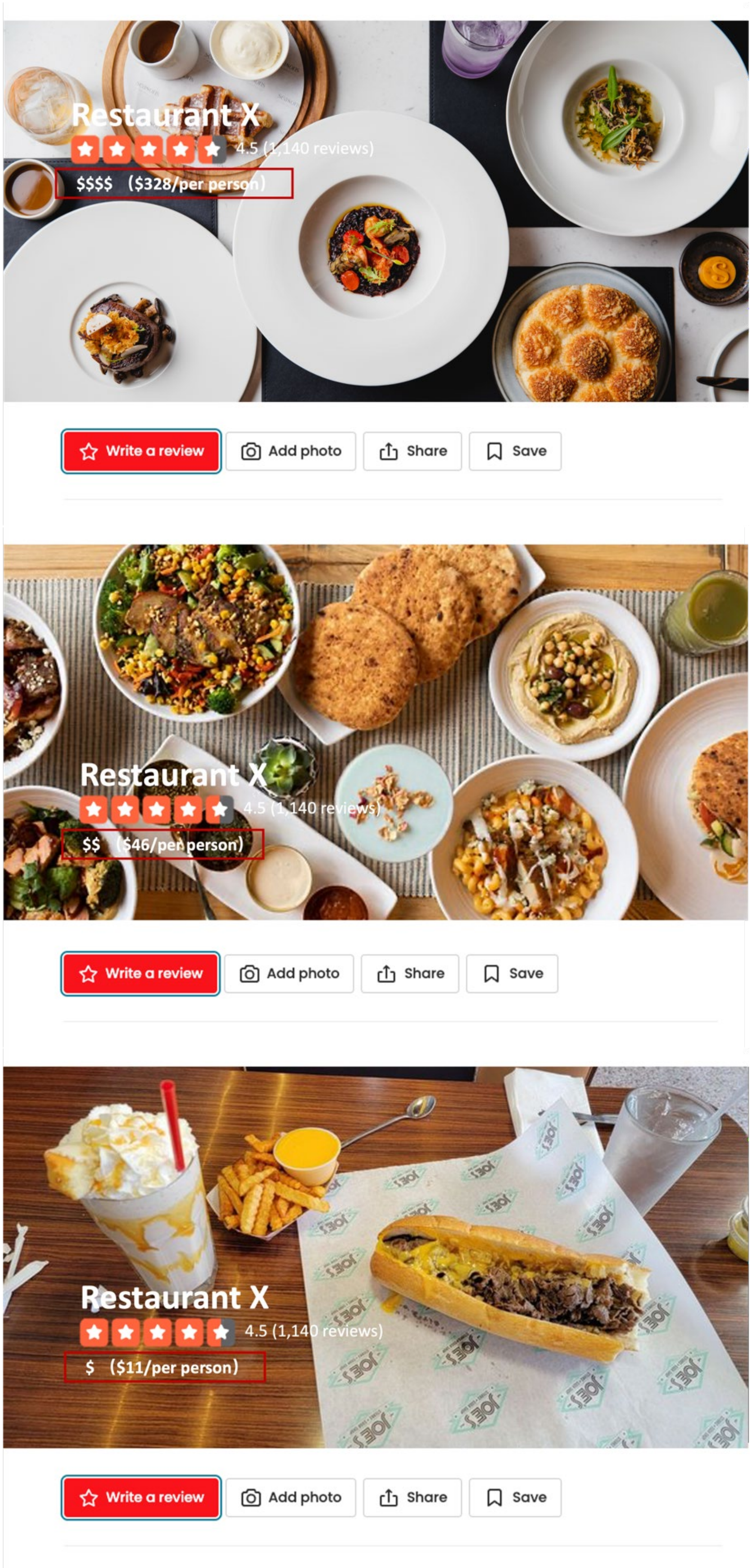

Figure F1. Manipulation of reviewed restaurant price level (Experiment 1)
Source: Created by author

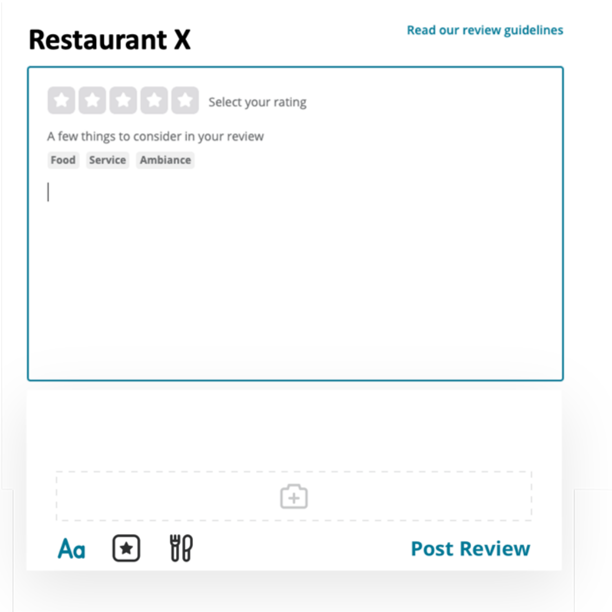

Figure F2. The review scenario

Source: Created by author

Conspicuous display measurement (Chaudhuri *et al*., 2011)

Posting more photos says something to people around me when I consume at this restaurant
I post more photos for this restaurant to show others that I am wealthy
I post more photos for this restaurant to showcase experiences from exclusive dining clubs or locations
I post more photos for this restaurant to show others that I have a good taste
I post more photos for this restaurant to show my friends that I am different
I post more photos for this restaurant to create my own style that everybody admires
I post more photos for this restaurant as it's the top-tier restaurants
I post more photos for this restaurant to show to others that I am sophisticated
I post more photos for this restaurant to show my social status symbol
Posting more photos for this restaurant is a symbol of success and prestige
I post more photos for this restaurant to show off, to be noted
Posting more photos for this restaurant means showing my prosperity
I post more photos for this restaurant because not many can afford it

Experiment 1 Result

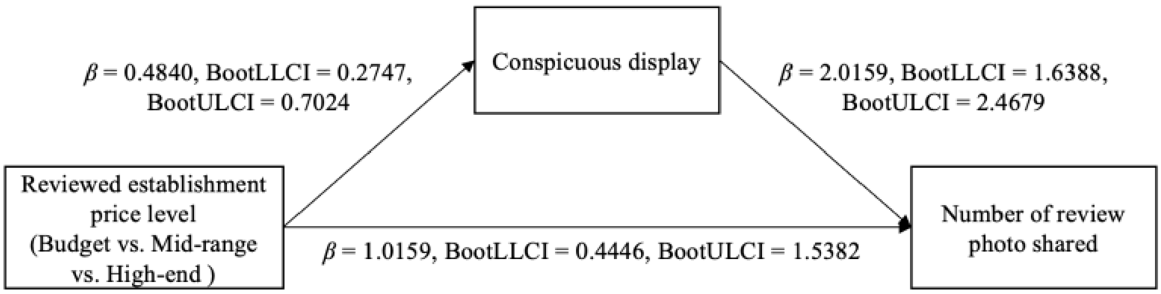

Figure F3. Mediating effect of conspicuous display

Source: Created by author

Experiment 2

Pretest Participants and Procedure

For the pretest of Experiment 2, we aimed to validate the manipulation of the user's social network size. A sample of 45 Mturk workers was recruited, with each participant randomly assigned to one of three conditions reflecting different levels of social network size (small, medium, large, see Figure F4 for experiment stimuli). Participants were shown mock social media profiles that depicted the varied sizes of social networks through the number of friends or followers listed. Participants were asked to assume these profiles were theirs. After reading the lead-in and viewing the given profile page, participants completed manipulation checks assessing their perception of their social network size. They were asked to rate the size of the social network associated with the profile they were assigned, using a 7-point Likert scale where 1 indicated 'Strongly disagree' with the statement "This profile has a large social network," and 7 indicated 'Strongly agree.'

Pretest Results

A one-way ANOVA revealed significant differences in the perceived sizes of the social networks among the three conditions ($F(2, 42) = 19.67$, $p < 0.01$), indicating that participants could accurately discern the small, medium, and large social network sizes as intended. This result confirms the effectiveness of our manipulation and sets the stage for the main experimental investigation.

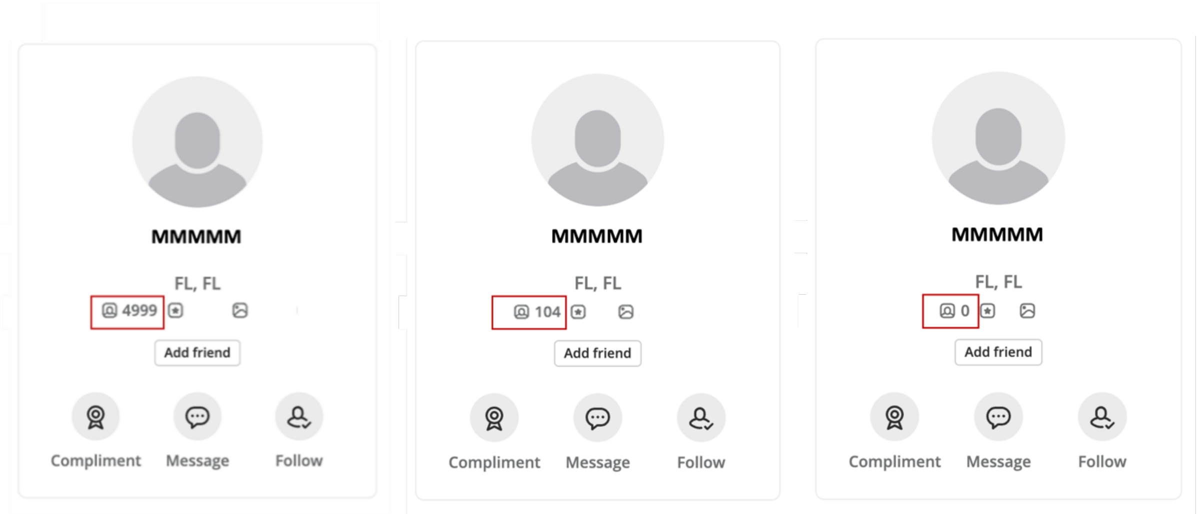

Figure F4. Manipulation of user social network size (Experiment 2)
Source: Created by author

Need for social approval measurement (Crowne and Marlowe, 1960)
I am motivated to post more photos if they garner attention from my social networks
Posting more photos in the review allows popularity among my social networks
Posting more photos in the review induces respect from my social networks
My decision to share photos with my reviews is influenced by my desire for social recognition
I feel by posting more photos in the review I can be more popular with my social networks
I feel it is easier to get noticed by my social networks when I post more photos in online review
I feel by posting more photos in the review I can describe to my social networks who and what I am

I post more photos in the review to obtain respect from my social networks
I post more photos in the review to increase my value in the eyes of my social networks
I post more photos in the review to attract the attention of my social networks
I post more photos in the review to create my own style that my social networks admires

Experiment 2 Result

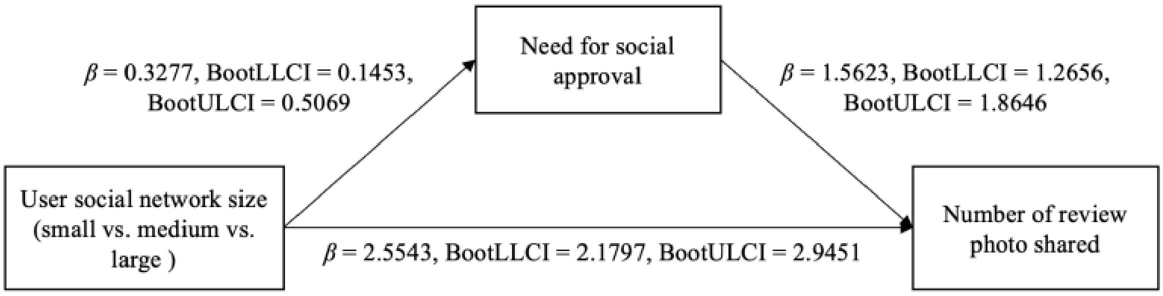

Figure F5. Mediating effect of need for social approval
Source: Created by author

Experiment 3

Pretest Participants and Procedure

In the pretest for Experiment 3 on user reputation status, 58 Mturk participants (M_{age} = 31.4, 57% female) were recruited to assess the manipulation of reputation status. We created the mock profiles reflecting each reputation status, manipulating with presence vs. absence of user elite badges (see Figure F6 for experiment stimuli). Participants were randomly assigned to one of two conditions: user profile with or without elite status. After examining the profiles, participants rated the perceived reputation level on a 7-point Likret scale, with anchors at 'Strongly disagree' and 'Strongly agree', to validate the manipulation's effectiveness.

Pretest Results

An independent-sample t-test confirmed the effectiveness of the reputation status manipulation. There was a significant difference in perceived reputation between the elite status group ($M_{\_elite}$ = 5.27) and the non-elite group ($M_{\_non\text{-}elite}$ = 2.04, t = 5.032, p < 0.01). This significant deviation from the neutral midpoint validates our stimuli, suggesting that participants could distinguish between profiles with and without elite status as intended.

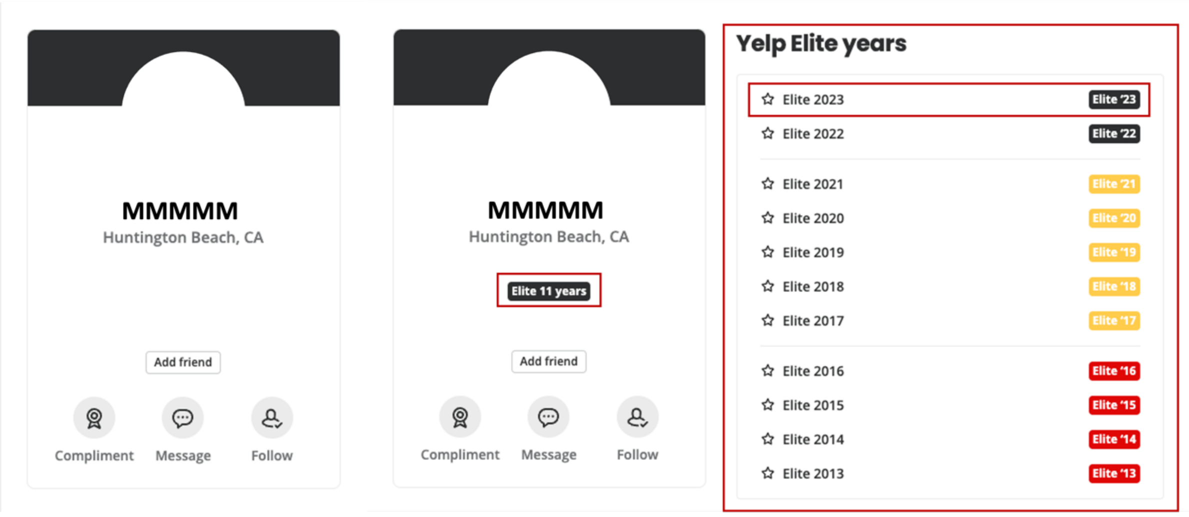

Figure F6. Manipulation of user elite status (Experiment 3)
Source: Created by author

Reputation seeking measurement (Wasko and Faraj, 2005)
I post more photos with my reviews to earn reputation in the review community
I post more photos with my reviews to gain recognition in the review community
I post more photos with my reviews to be an elite member in the review platform

Experiment 3 Result

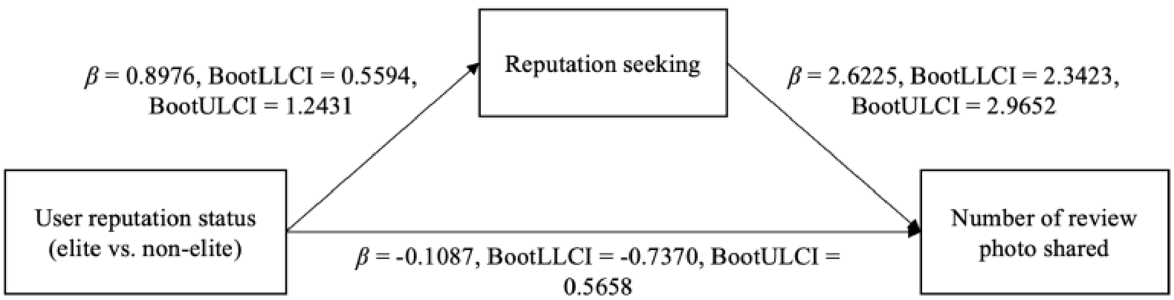

Figure F7. Mediating effect of reputation seeking
Source: Created by author