# WHEN DO WE LISTEN TO SOCIAL INFLUENCERS? TWO ESSAYS EXAMINING THE ROLE OF SOCIAL INFLUENCE


by

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**WHEN DO WE LISTEN TO SOCIAL INFLUENCERS? TWO ESSAYS EXAMINING THE ROLE OF SOCIAL INFLUENCE**

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In Essay 1, I examine influencer marketing strategies and their impact on online brand engagement. Influencer marketing is prevalent in firm strategies, yet little is known about the factors that drive success of online brand engagement. The study sheds light on influencer marketing and examines how sponsored bloggers influence consumers at different stages of the consumer purchase funnel. The findings suggest that sponsored blogging affects online engagement (e.g., posting comments, liking a brand) differently depending on blogger characteristics and blog post content, which are further moderated by social media platform type and campaign advertising intent. When a sponsored post occurs on a blog, high blogger expertise is more effective when the advertising intent is to raise awareness versus increase trial. However, source expertise fails to drive engagement when the sponsored post occurs on Facebook. When a sponsored post occurs on Facebook, posts high in hedonic content are more effective when the advertising intent is to increase trial versus raise awareness. Effectiveness of campaign incentives is dependent on the platform type, such that they can increase engagement on blogs but decrease engagement on Facebook. The empirical evidence for these findings comes from real in-market customer response data and is supplemented with data from an experiment. Taken together, the findings highlight the critical interplay of platform type, campaign intent, source, campaign incentives, and content factors in driving engagement. The authors discuss managerial implications of their findings on the implementation of influencer marketing strategies.

In Essay 2, my research examines how group norms are determined in a sequential choice setting. When people in groups make decisions sequentially, they are conforming to group norms as they develop. I show that the group norm is determined by the behavior of the second person (i.e. the first follower) relative to the first person (i.e. the leader). In Study 1, a restaurant field study, I show that people either order to fulfill uniformity or variety depending on the behavior of the first follower relative to the group leader. When the first follower chooses similarly (differently) to the leader, the rest of the group seeks uniformity (variety). In Study 2, I use a secondary data set of online reviews to demonstrate that group variation in review valence depends on the comparison of the first follower's review relative to the leader's review. In Study 3, I replicate the findings in an experimental setting and show that perceptions of a group norm mediate the effect of the first follower on within-group variation. Implications for research and practice are discussed.

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# 1.0 INTRODUCTION

Why do we listen to social influencers? Two essays seek to answer this question in terms of online social media influencers, as well as determining the influential decision-maker in online and offline group behavior. Social influencers are an extremely valuable asset for companies, advertisers, and organizations, but current research has not examined under which conditions certain social media influencers outperform others. Current research has also not examined the influential decision-maker for determining group norms in sequential choice settings. For my dissertation, I will demonstrate the role of social influencers, both online and offline, in the context of influencer marketing and normative group influence.

Essay 1, "Driving Brand Engagement Through Online Social Influencers: An Empirical Investigation of Sponsored Blogging Campaigns," examines how and why influencer marketing strategies affect online engagement. The central proposition in this work is that information presented to consumers by sponsored bloggers affects online engagement (e.g., comments, likes) differently, depending on blogger characteristics and post content, and that these effects vary according to the type of social media platform and advertising goals. The framework draws from psychological theories of persuasion, including the persuasion knowledge and elaboration likelihood models, to explain the effect of platform involvement. The results show that in awareness campaigns, emphasizing peripheral cues (e.g., blogger expertise, campaign incentives) is beneficial, whereas in trial campaigns, focusing on information content and characteristics (i.e., hedonic value) can induce engagement with a blog post. Furthermore, this work demonstrates that for sponsored blogging campaigns to maximize their impact, posts on low-involvement platforms (e.g., Facebook) should emphasize network size. The findings shed light on the factors that govern how influencer campaigns elicit consumer engagement, thus offering important managerial and theoretical insights into influencer marketing approaches and online brand engagement. This essay has the potential for many future research directions, including work on the effectiveness of micro versus macro influencers.

Essay 2, “Setting Sequential Group Norms: How the First Follower Determines the Trend,” proposes that the behavior of the second contributor in the group, i.e. the “first follower,” plays the pivotal role in determining group norms in a sequential group choice setting. While the leader has the power to make the first decision, it is not until that behavior is emulated by the first follower that a norm is enacted. My research shows that the behavior of the first follower, versus the leader, can determine this group norm in sequential choice. Specifically, I propose that the behavior of the first follower, whether choosing conformity or divergence, from the leader will determine the group norms for decisions in the remainder of the group. If the first follower chooses conformity (divergence), then the remainder of the group will seek conformity (divergence) to match the group level goal of self-presentation. In this essay, I analyze data from a large secondary dataset of Yelp reviews, a field study at a restaurant, and an experiment, to demonstrate the process and establish causation.

This dissertation contributes to both theory and practice in several important ways. The first essay contributes to the online influencer marketing literature. Despite its growing importance, sponsored blogging is an underdeveloped research area. Research to date has focused overwhelmingly on sponsorship disclosures and their impact on various consumer-level metrics, such as behavioral intention, attitude, credibility, and trust (Ballantine and Yeung 2015; Colliander and Erlandsson 2015; Hwang and Jeong 2016; Lu, Chang, and Chang 2014). In contrast, my work provides a comprehensive framework of success factors in influencer marketing campaigns that can be used by practitioners and academics.

In addition, the second essay contributes to literature on social influence in which there is a sequential process of expressing behaviors. To my knowledge, this is the first paper to examine the process underlying the formation of group norms in a sequential choice setting. Past research has demonstrated that the goal of seeking variety versus uniformity depends on the culture, i.e. collectivist or individualistic (Markus and Kitayama 1991; Yoon et al. 2011). Other research has stated that individuals seek more variety in a sequential choice setting than they would making decisions in isolation (Ariely and Levav 2012). Ariely and Levav (2012) seem to suggest that all members of the group contribute equally to the overall group decision strategy, however, I demonstrate that it is the first follower, or the second decision maker, who is the key influencer. Importantly, I not only qualify their findings, but I further demonstrate its application in online behavior.

## 2.0 ESSAY 1: DRIVING BRAND ENGAGEMENT THROUGH ONLINE SOCIAL INFLUENCERS: AN EMPIRICAL INVESTIGATION OF SPONSORED BLOGGING CAMPAIGNS

With consumers increasingly relying on peer-to-peer communications, influencer marketing has continued to grow in importance as a key component of firms' digital marketing strategies (Association of National Advertisers 2018). Nearly 75% of marketers today are using influencers to spread word of mouth (WOM) about their products and brands on social media. Influencer marketing is often considered critical to strengthening online brand engagement (Newberry 2018). Consequently, 65% of multinational brands have indicated plans to increase spending on influencer marketing, with influencer marketing spend expected to reach $10 billion by 2020 (Belton 2019; Mediakix 2018). However, despite the explosion of these social influencers, their effectiveness is still low; for an influencer on Facebook, the average engagement rate per post is .37%; on Twitter, it is even lower at .05% (Rival IQ 2018).

A large and important category of influencer marketing is sponsored blogging, in which companies solicit bloggers to post about specific products and brands (i.e., "sponsored posts") (Linqia 2018). Bloggers can help generate WOM about a brand, product, or service directly through the content of their sponsored posts. Firms have deployed sponsored blogging both successfully (i.e., Nokia's camera phone campaign in Finland) and unsuccessfully (i.e., Dr Pepper's "Raging Cow" campaign) (Corcoran et al. 2006). However, we need to develop a better understanding of what drives the success of influencer marketing as a whole and sponsored blogging in particular. Given the significant marketing expenditures dedicated to this strategy and a paucity of knowledge regarding success drivers, this is an important research gap worth addressing.

Sponsored blogging is a hybrid approach combining aspects of paid and earned media (e.g., Colicev et al. 2018; Lovett and Staelin 2016). We distinguish this phenomenon from a purely paid media strategy because influencers engage in WOM and have control over the ultimate message of the advertisement. As companies reimburse bloggers (with either cash or free goods) to generate posts on social media, influencer marketing is distinct from organically generated WOM. Because influencer marketing blends elements of paid and earned media, we can distinguish this from prior research focusing on paid and owned media (e.g., Lovett and Staelin 2016, de Vries, Gensler, and Leeflang 2017) or earned media, including online WOM (e.g., Hewett et al. 2016). We also extend the traditional advertising literature on the impact of source credibility and message content (Grewal et al. 1997).

We provide a comprehensive framework examining the drivers of sponsored blogging strategies, including blogger characteristics, content characteristics, and campaign incentives, and this contributes to the literature in three ways. First, this study advances prior research by examining how social influencers (or sponsored bloggers) can affect consumers at different stages of the consumer purchase funnel by examining different campaign intents (e.g., awareness vs. trial). Second, this research sheds light on the important role of campaign intent as a moderator of the impact of blogger (e.g., expertise) and content (e.g., hedonic value) characteristics on social media engagement. Third, we suggest that the type of social media platform (blogs vs. Facebook) can moderate the impact of these factors on engagement.

Our findings demonstrate that in a blog context, blogger expertise, campaign intent, hedonic value of post, and campaign giveaway are key drivers of engagement. Additionally, blogger expertise exerts a greater impact in awareness (vs. trial) campaigns. On Facebook, hedonic value exerts a positive impact and trial campaigns benefit more from use of hedonic content. Campaign giveaway exerts a negative impact pointing to potential cannibalizing role of one platform on another (blog versus Facebook). Taken together, the findings shed light on various factors that govern how influencer campaigns elicit consumer engagement across multiple platforms. Figure 1 presents our conceptual framework.

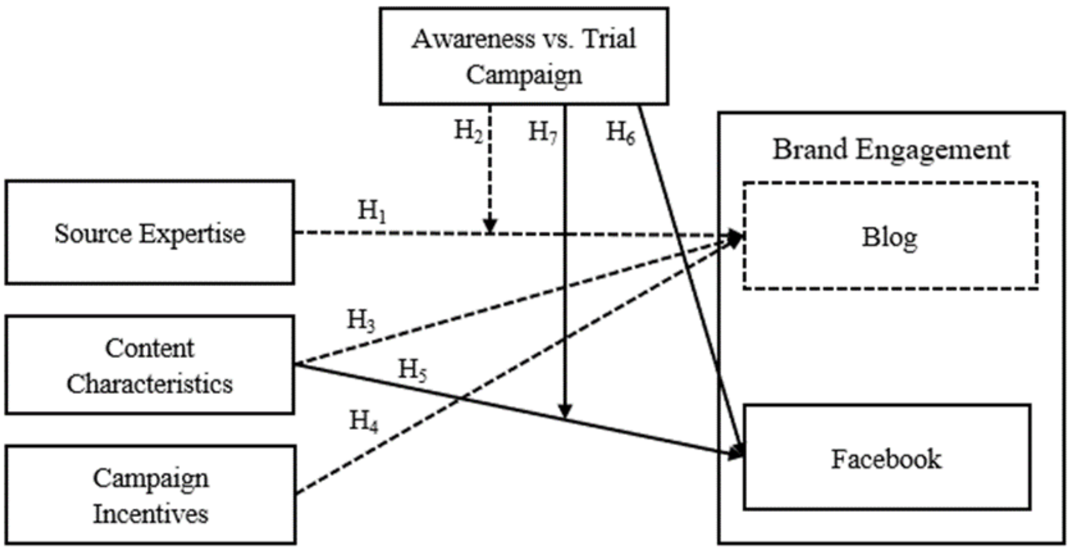


**Figure 1: Conceptual Framework of Factors Influencing Sponsored Blogging Campaign Effectiveness**

This research uses real in-market customer response data, assembles a large data set of sponsored blogging campaigns, measures various characteristics, and links these to concrete brand engagement outcomes. Thus, our field data provide a unique vantage point and draw a richer picture of not only what constitutes an effective influencer marketing campaign but also how this varies across social media platforms. We supplement the findings by collecting data in a lab study.

## 2.1 Theoretical Background and Hypotheses

### 2.1.1 Engagement

Our key dependent variable for the primary field study is social media engagement. We define engagement as a "customer's cognitive, emotional, and behavioral activities" (Hollebeek 2011,

p. 555). More specifically, our focus is on indirect customer engagement, which includes incentivized referrals, social media conversations about products/brands, and customer feedback to companies (Pansari and Kumar 2017). These types of actions contribute to a firm's revenue, as referred customers are typically more profitable than those not referred (Palmatier, Kumar, and Harmeling 2017; Schmitt, Skiera, and Van den Bulte 2011; Van den Bulte et al. 2018). This impact of engagement on profitability has also received empirical verification across business-to-business (Kumar, Petersen, and Leone 2010) and business-to-consumer (Lee and Grewal 2004) contexts, and its benefits are shown to derive from both cost reduction and revenue enhancement (Harmeling et al. 2017).

Consumer engagement literature highlights several potential factors that may influence consumer engagement, including emotionality, direct firm actions, and product involvement (Harmeling et al. 2017; Pansari and Kumar 2017). We derive our key factors from this literature, and add new factors, such as overall campaign intent, characteristics of the influencer (i.e., source expertise and post content), and level of involvement elicited by the social media platform. The customer engagement activity we focus on is social media interactions with sponsored influencer content, and we operationalize this as likes and comments on sponsored posts. We next derive our key hypotheses for each of the two platforms we analyze in the field study.

### 2.1.2 Blogging Platform

Research on influencer marketing examines elements of sponsored advertising, product type, source characteristics, and sponsorship disclosure. Regarding product type, Zhu and Tan (2007) find that for low-involvement (vs. high-involvement) products, low-expertise bloggers have greater success when they are explicit about campaign intentions. Fu and Chen (2012) assess the impact of customer comments, customer involvement, and informational (vs. emotional) appeals on consumer attitude and find that customer involvement has a moderating impact on attitude. Uribe, Buzeta, and Velásquez (2016) demonstrate that communicator expertise, two-sided messages, and nonsponsored messages have positive impacts on credibility and behavioral intention. Van Reijmersdal et al. (2016) show that sponsorship disclosures result in readers using resistance strategies, such as counterarguing. Table 1 provides a review of research on the key variables of influencer marketing, and Table 2 summarizes the key findings.

**Table 1: Previous Research Related to Sponsored Blogging Key Variables**

| Authors (Year) | Independent Variables | | | | | | | | | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Blogger Characteristics | Audience Characteristics | Product Type | Sponsorship Disclosure | Network Characteristics | Post Content | Brand Awareness | Campaign Intents | Reader Review Valence | Behavioral Intention | Attitude | Effectiveness | Credibility | Trust | Engagement |
| Zhu and Tan (2007) | ✓ | | ✓ | ✓ | | | | | | ✓ | ✓ | | | | |
| Magnini (2011) | | | | ✓ | | | | | | | | ✓ | | ✓ | |
| Fu and Chen (2012) | | ✓ | | | | | | | ✓ | | ✓ | | | | |
| Lu, Chang, and Chang (2014) | | | ✓ | ✓ | | | ✓ | | | ✓ | ✓ | | | | |
| Colliander and Erlandsson (2015) | | | | ✓ | | | | | | | ✓ | | ✓ | | |
| Ballantine and Yeung (2015) | | | | ✓ | | | | | ✓ | ✓ | ✓ | | ✓ | | |
| Hwang and Jeong (2016) | | | | ✓ | | | | | | | | | ✓ | | |
| Rooderkerk and Pauwels (2016) | ✓ | | | | | ✓ | | | | | | | ✓ | | ✓ |
| Uribe, Buzeta, and Velásquez (2016) | ✓ | | | ✓ | | ✓ | | | | ✓ | | ✓ | ✓ | | |
| Van Reijmersdal et al. (2016) | | | | ✓ | | | | | | ✓ | ✓ | | | | |
| Hollebeek and Macky (2019) | | | | | | ✓ | | ✓ | | | | | | ✓ | ✓ |
| **This study** | ✓ | | | | ✓ | ✓ | | ✓ | | ✓ | | | | | ✓ |

**Table 2: Previous Research Related to Sponsored Blogging Key Findings**

| Year | Authors | Domain | Key Findings |
|---|---|---|---|
| 2007 | Zhu and Tan | Blog advertising | For low-involvement products, low-expertise communicators have better advertising effectiveness when explicit about their campaign intent. For high-involvement products, communicators who are implicit about their campaign intent have better advertising effectiveness. |
| 2011 | Magnini | Company-sponsored messages | Service firms disguise sponsored messages as unsponsored WOM because genuine WOM has greater effectiveness. |
| 2012 | Fu and Chen | Blog advertising | Information appeals work best for customers with high involvement and emotional appeals for customers with low involvement. The quality and proportion of negative comments affect attitudes of customers. |
| 2014 | Lu, Chang, and Chang | Sponsored blogging | Consumers have positive attitudes and improved purchase intentions when reading sponsored blog posts for search goods or products with high brand awareness. |
| 2015 | Colliander and Erlandsson | Sponsored blogging disclosure | More negative attitudes toward sponsored blogs with disclosure versus sponsored blogs without disclosure. |
| 2015 | Ballantine and Yeung | Organic and sponsored blogging | Effects of review valence on perceived credibility, brand attitude, and behavioral intentions do not differ between organic and sponsored blog posts. |
| 2016 | Hwang and Jeong | Sponsored blogging | Sponsorship disclosure on blog posts has a negative impact on credibility, unless the disclosure includes the additional disclaimer of "all opinions are my own." |
| 2016 | Rooderkerk and Pauwels | Online discussion forum | The readability of the post, the controversiality of the content and the status of the post author have the highest elasticity on the number of comments that a post receives on an online discussion forum. |
| 2016 | Uribe, Buzeta, and Velásquez | Blog advertising | Use of a two-sided message versus a one-sided message, expert sources, and nonsponsored messages is more effective in terms of increasing source credibility and behavioral intention. |
| 2016 | Van Reijmersdal et al. | Sponsored blogging | Sponsored blogging disclosures induce people to use resistance strategies, such as counterarguing and negative affect. |
| 2019 | Hollebeek and Macky | Brand related content | A conceptual framework that identifies important consumer-based Digital Content Marketing antecedents, including uses-and-gratifications (U&G)-informed functional, hedonic, and authenticity-based motives for DCM interactions. |
| *2019* | *This Study* | *Sponsored blogging* | *Impact of source, network, and post characteristics varies depending on type of social media platform and campaign intent. Expertise is only important for high-involvement platforms.* |

### 2.1.3 Campaign Intent

Broadly, influencer marketing campaigns have two goals: (1) to increase awareness and (2) to encourage trial. From a marketer's perspective, awareness campaigns are an easier-to-achieve goal and do not require any overt action on the part of consumers. Trial campaigns, which encourage consumers to make a purchase, are typically linked to consumer actions (e.g., purchase, app download) and therefore have a more overt persuasion intent and also a higher hurdle to generate customer engagement. These advertising goals (awareness vs. trial) can also affect the persuasion knowledge of consumers, depending on whether there is a more direct advertising motive, as in the case of a trial campaign, or a less direct advertising motive, as in the case of an awareness campaign.

These campaign intents align with the beginning and end of the consumer's decision journey, which typically involves multiple stages in a hierarchy-of-effects, such as awareness, knowledge, liking, preference, conviction, and purchase. Prior research has examined this dichotomy of awareness versus trial intent in a traditional advertising context (e.g., Muller 1983). We propose that campaign intent is a potential moderator that can influence engagement differently depending on the stage of the decision journey.

### 2.1.4 Blogger Expertise

Source expertise refers to the level of credibility a source possesses. In the source credibility literature, expertise reflects the extent to which a consumer is qualified to discuss a subject (Alba and Hutchinson 1987). Berlo, Lemert, and Mertz (1969) include source qualification as part of their definition of source expertise. Competence, knowledge, education, expertise, and the ability to share knowledge are all qualities of expert power (Hinkin and Schriesheim 1989). This can derive from informational power, in which the expert has knowledge that others do not have (Deutsch and Gerard 1955). French and Raven (1959) define expert power as knowledge within a domain (e.g., law). Endorsers are more likely to be considered experts if they are competent and have relevant knowledge (Homer and Kahle 1990).

Prior communication literature indicates that source expertise exerts an important impact on attitude change (Hovland and Weiss 1951; McCracken 1989; Ohanian 1991). Source expertise also leads to higher levels of persuasion (Petty and Wegener 1998), and behavioral changes (Crisci and Kassinove 1973). Woodside and Davenport (1974) show that consumer purchase was higher for an expert than a nonexpert salesperson. Expertise enhances the credibility of the source, which in turn enhances persuasive messages even when the message is not relevant (Petty and Cacioppo 1986). Higher source expertise leads to deeper processing, which results in stronger persuasion (Homer and Kahle 1990). In an influencer marketing context, expertise increases behavioral intention toward products (Uribe, Buzeta, and Velásquez 2016). In a sponsored blogging context, consumers will prefer products endorsed or referred by a blogger with expertise (because consumers perceive the message as more persuasive and credible (Zhu and Tan 2007, Kiecker and Cowles 2002). Thus:

$H_1$: Blogger expertise has a positive impact on blog engagement. The higher the blogger's expertise, the higher is the number of blog post comments.

Despite the expected positive impact of blogger expertise on engagement in a sponsored blogging context, source expertise can also have a neutral (or even negative) effect in some situations. Prior research suggests that in the presence of an extreme advertising claim, the positive impact of source expertise diminishes (Goldberg and Hartwick 1990). Tormala, Briñol, and Petty (2007) show that source credibility influences the amount and positivity of thinking.

Depending on the context, type of claim, and stage in the decision-making process, source expertise may even have a nonsignificant (or negative impact) on engagement.

The nonsignificant impact of source expertise also stems from the countervailing positive impact of low-expertise bloggers (novice endorsers). Novice endorsements can be as effective as those from experts (Frieden 1984; Wang 2005). This enhanced effectiveness of novice endorsers comes from their ability to generate greater trust in their audiences, due to greater perceptions of similarity of low expertise. Zhu and Tan (2007) find that for certain (i.e., low-involvement products), low-expertise bloggers have greater success when they are explicit about campaign intentions. Thus, greater trust generated by low-expertise or novice bloggers may account for their increased effectiveness under certain conditions (e.g., campaign intent, platform involvement), such that they are equally effective as expert bloggers. Given these mixed findings, we hypothesize that the effect of blogger expertise on blog engagement may vary depending on campaign intent.

### 2.1.5 Blogger Expertise Based on Campaign Intent

Both high- and low-expertise bloggers may be considered influential, under varying circumstances. As noted previously, in the presence of an extreme advertising claim, the positive impact of source expertise diminishes (Goldberg and Hartwick 1990). Awareness-building campaigns give no overt encouragement to make a purchase, resulting in lower levels of persuasion knowledge and consumer skepticism. These lower levels may induce consumers to be more open to processing information from high-expertise bloggers, which leads to their greater influence. This idea is in line with prior research suggesting that in early stages of decision making, expertise becomes a more important influencer for persuasion than homophily (Wang et al. 2008). Therefore, we expect blogger expertise to vary in its impact depending on campaign intent, such that high-expertise perceptions translate into higher engagement in awareness (vs. trial) campaigns.

By contrast, novice (or low-expertise) bloggers attain their persuasiveness from their ability to engender high levels of trust among audiences. This trust elicited by low-expertise bloggers may be more important in a trial setting because of higher persuasion knowledge and consumer skepticism. Wang et al. (2008) demonstrate that the likelihood to act on advice was higher when participants perceived more similarity to the source of information (i.e., higher homophily). In line with this reasoning, audiences may perceive a source with higher expertise as less similar (i.e., less homophilous). Rosario et al. (2016) note that the effectiveness of online WOM on social media platforms is stronger when receivers can assess their own similarity to senders. Thus, we expect that less expert (i.e., more homophilous) bloggers will be more effective in trial (vs. awareness) campaigns. In turn, this pattern of effects will result in a differential impact of higher blogger expertise based on campaign intent, as outlined below.

$H_2$: Campaign intent moderates the impact of blogger expertise on brand engagement in a blog platform. Specifically, (a) when blogger expertise is high, awareness campaigns are more effective in generating brand engagement; (b) when blogger expertise is low, trial campaigns are more effective at generating brand engagement.

### 2.1.6 Hedonic Value of Post

The hedonic value of a post refers to the enjoyment, emotions, and entertainment a consumer experiences from reading the post. Evidence suggests that hedonic content can have an impact on attitudes and WOM (Berger and Schwartz 2011; Kim, Ratneshwar, and Thorson 2017). In a traditional advertising context, researchers have shown that hedonic value captures attention (Teixeira, Picard, and El Kaliouby 2014) and influences attitude toward an ad (Kim, Ratneshwar, and Thorson 2017). In an online setting, the presence of hedonic content positively affects viral marketing message success on Facebook (Chiu et al. 2007). Berger and Milkman (2012) suggest that in an online context, specific emotions (e.g., awe, anxiety) trigger arousal, which in turn results in greater virality of online content. Ordenes et al. (2019) extend these findings and argue that consumers share expressive or assertive brand messages more frequently than directive brand messages. Relatedly, Herhausen et al. (2019) indicate that hedonic content can be a key factor in the virality potential of online firestorms. Building on these findings, we expect a post featuring high hedonic value content to increase arousal, deepening customer engagement. Therefore, we posit a general positive impact of hedonic content on the blogging platform.

$H_3$: Post content, in terms of hedonic value, is positively related to engagement in blog post comments.

### 2.1.7 Campaign Incentives

Campaign incentives are marketing actions designed to elicit specific responses and engagement from consumers. The purpose of a campaign incentive is "to give followers a free item (or a chance to win a free item) in exchange for them sharing, liking, following, and/or reposting a picture" (Nilo 2017). For example, Rafflecopter is a giveaway platform widely used by sponsored bloggers, and the requirements to enter each giveaway are at bloggers' discretion. For some campaign giveaways, bloggers require consumers to comment on the blog post itself, while others require a different action (e.g., become a Twitter follower, share the giveaway) to enter the giveaway.

Campaign incentives are a direct firm action to increase customer engagement (Verhoef, Reinartz, and Krafft 2010). Other benefits of giveaways include an increased desire to buy more, higher-quality perceptions of the product, and increased WOM about the product (White 2013). In Berger and Schwartz's (2011) study, consumers who received a free product talked about it 20% more than those who did not receive the product for free. Therefore, we expect the presence of incentives to increase blog engagement because they elicit consumer comments for a chance to win the giveaway.

$H_4$: Campaign incentives are positively related to engagement, such that inclusion of a campaign incentive leads to more blog post comments.

## 2.2 Influencer Marketing on the Facebook Platform

Firms often launch influencer marketing campaigns on multiple platforms simultaneously. The blog platform constitutes the primary environment for sponsored bloggers to exert their influence. People who choose to interact with bloggers and their postings are typically followers of the blogger. Followers have opted to obtain information posted by bloggers and therefore are likely highly involved in the environment. This higher involvement translates into several facets of blog campaigns that help strengthen engagement.

### 2.2.1 Platform Differences

Platforms differ in their level of distraction and targeted goals. Level of involvement can vary across platforms such as print media versus television (Worchel, Andreoli, and Eason 1975), suggesting that social media platforms can also trigger different levels of involvement. Customer engagement literature identifies customer involvement as an important antecedent of engagement; higher involvement can motivate consumers to search for information and moderate customer engagement (Pansari and Kumar 2017). A blogging campaign involves blog posts to audiences that have opted into a particular group, and these members seek out specific information on blogs. However, bloggers typically include links to their blog posts on other social media venues (e.g., Facebook). Platforms such as Facebook are relatively less involving and more distracting for each individual post because of the large amount of information and content provided (Yahyapour Jalali 2015). Therefore, we examine whether the platform on which the audience interacts with the blogger's post has an impact on post engagement.

In high-involvement (low-distraction) environments, argument quality has a greater impact on persuasion, while in low-involvement (high-distraction) environments, heuristic cues are likely to be most important and cognitive factors least important which is consistent with the basic tenets of the Elaboration Likelihood Model (ELM) (Petty and Cacioppo 1986). In line with this argument, research indicates that when consumers are less involved with products, they use peripheral routes to process information (Fu and Chen 2012). For a low-involvement (high-distraction) platform such as Facebook, peripheral cues, such as the size of the blogger network and hedonic value, should be important. Conversely, for a low-distraction (high-involvement) platform such as blogs, source expertise and post content should play a more important role in eliciting engagement. However, the difference in these platforms is also likely to depend on the extent to which Facebook complements influencer marketing campaigns primarily based on blog posts. Although these media are highly complementary, in some situations (e.g., campaign giveaways), blogs may cannibalize Facebook engagement. We articulate these differences using a pretest but clarify them in our separate predictions we develop for blogs and Facebook platforms.

### 2.2.2 Pretest of Social Media Platform Differences

To provide a priori evidence of differences in social media platforms, we pretested the levels of distraction across blogs and Facebook, using a survey of participants (N = 264) on Amazon Mechanical Turk. Participants ($M_{age}$ = 35.2 years, 50.0% male) were randomly assigned to one of two conditions. In the blog condition, we asked participants to recall the last time they were on a blog page. In the Facebook condition, we asked participants to recall the last time they were on Facebook. First, we measured how distracted they felt, on a scale from 0% to 100%. The regression model, controlling for age and gender, was significant ($F(3, 260) = 7.22$, $p < .01$). We found significant differences between the blog and Facebook environments ($M_{Blog} = 32.65$ vs. $M_{Facebook} = 42.83$; $b_{platform} = –10.67$, $p < .01$). Second, we examined the degree to which participants were looking for specific content on the platform and, after controlling for age and gender, found a significantly higher amount of content-seeking in blog than Facebook posts ($M_{Blog} = 59.19$ vs. $M_{Facebook} = 48.14$; $b_{platform} = 11.25$; $F(3, 260) = 3.61$, $p < .01$). These results lend support to our argument that platform distraction and content search differ between blogs and Facebook, with distraction being lower and content-seeking being more common on blogs.

Therefore, based on the pretest, we conclude that a key distinction between Facebook and blogs is that Facebook is a high-distraction environment, which results in low-involvement-type processing of information about blog posts. Thus, peripheral cues should exert a positive impact on low-involvement platforms such as Facebook (Chaiken 1980; Petty and Cacioppo 1986), leading to a positive impact of peripheral cues (e.g., number of followers, hedonic content, timing and number of posts).

We argued previously that higher and lower blogger expertise may vary in their impacts on brand engagement depending on campaign intent (awareness vs. trial), having a positive impact under an awareness intent and a negative impact under a trial intent. The Facebook platform induces a different kind of processing, in that the source information for blog posts (i.e., blogger expertise) receives less extensive scrutiny. Therefore, we argue that our hypothesized pattern of effects regarding blogger expertise on the blog platform will not hold for Facebook.

### 2.2.3 Hedonic Value on the Facebook Platform

Evidence shows that engagement on Facebook is related to hedonic content (Chiu et al. 2007). The primary rationale for this is that the hedonic value of content generates an emotional response (Dobele et al. 2007), which leads to higher arousal and a greater propensity to like and share in online settings (Berger and Milkman 2012; Fiore, Jin, and Kim 2005). Consequently, we anticipate that hedonic content associated with blog posts is highly relevant to low-involvement platforms such as Facebook, as it helps overcome low involvement by raising the interestingness of a post. In support of this idea, the in-store shopping literature (e.g., Babin and Attaway 2000) shows that hedonic value of a shopping experience plays a key role in elevating involvement and inducing purchase behavior. Thus:

$H_5$: The hedonic value of blog posts has a positive impact on Facebook engagement (i.e., likes).

### 2.2.4 Campaign Intent on the Facebook Platform

The importance of hedonic value may vary depending on campaign intent. In trial campaigns, we expect Facebook participants' willingness to engage in campaigns with overt commercial intent to be low. Karal and Kokoç (2010) propose that the primary motivations for Facebook usage are to gain knowledge, acquire new connections and to strengthen existing relationships. An overtly commercial intent, as in the case of trial, can interfere with the intended usage of the platform and therefore be met with resentment by users. Since gaining knowledge and encountering ideas and information are reasons to use Facebook, these are more in line with the awareness intent; the awareness intent is more of a helping motive associated with WOM communications in the network. Facebook users may spread WOM about awareness campaigns because it generates positive feelings and strengthens social connections (Hennig-Thurau et al. 2004). Thus:

$H_6$: Campaign intent has a positive impact on engagement on Facebook platforms. Specifically, awareness (vs. trial) campaigns generate more Facebook engagement (i.e., likes).

### 2.2.5 Interaction of Hedonic Value with Campaign Intent on Facebook

In addition to the preceding main effect predictions, we anticipate an interaction effect of hedonic value and campaign intent on Facebook engagement. In online settings, research reveals that consumers often make purchases when the shopping experience is highly entertaining and not routine (Kim 2002; Mathwick, Malhotra, and Rigdon 2001), thus suggesting that when campaigns involve purchasing (e.g., trial), the hedonic value of the blog post will be valuable. Research on hedonic content in the context of email sharing (Chiu et al. 2007) finds that a hedonic message appeal leads to a greater likelihood of forwarding the message. Berger and Milkman (2012) show that high arousal content is always likely to be shared, though they find this only in an email context, which is a private form of sharing. In contrast with these findings, Tucker (2014) suggests that hedonic content does not universally result in sharing and that context must be considered along with the type of outcome being studied. In line with this view, we argue that hedonic content varies in its usefulness on sharing platforms such as Facebook. Furthermore, the highly hedonic content we examine is *sponsored* content written by influencers, which is distinct from both email and news articles.

In the context of sponsored blogs (with a potential to induce skepticism given its commercial nature), hedonic content may not always contribute to higher sharing and may only help elevate interest in otherwise less engaging content (e.g., trial campaigns). In these settings, hedonic content may provide a rationale for sharing messages that may otherwise not receive customer attention. We base our argument on prior research that shows that hedonic value is beneficial in online shopping contexts because it raises involvement in an otherwise low-involvement activity (Bridges and Florsheim 2008; McMillan, Hwang, and Lee 2003). This finding suggests that hedonic value will be more beneficial in trial than awareness campaigns. Unique, warmhearted, or interesting blog posts (all characteristics of high-hedonic-valued blog posts) can give Facebook users a rationale for sharing otherwise undervalued commercial content, allowing for greater virality of influencer marketing posts with a trial intent. Thus:

$H_7$: Campaign intent moderates the impact of hedonic value on engagement. High (vs. low) hedonic value has a more positive impact on trial campaigns than awareness campaigns.

## 2.3 Study 1

### 2.3.1 Data

The data come from a leading agency for sponsored blogging campaigns[1] that focuses on "mommy" bloggers. The data consist of 1,830 sponsored posts written by 595 bloggers, collected from September 2012 to December 2016.[2] These blog posts came from 57 different campaigns,

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[1] We withhold the name of the agency for privacy reasons.

[2] As we subsequently describe, the data on blog posts involved coding across a variety of independent and dependent variables. In the process of coding data pertaining to the variables, we encountered some missing information for a few variables. Thus, our final sample size for analysis is 1,237.

including Awesome Avocados, Banner Alzheimer, Chef Boyardee Little Chef, Latte Love, and Barnes & Noble.

For each campaign, companies work with the blogging agency to coordinate campaign details, such as the intended message, target audience, and goals. Bloggers are recommended for the campaign on the basis of their demographics, age of children, and expertise, and they can choose to work on projects in line with their interests, availability, and willingness to work within the set budget. Bloggers are required to disclose that they are sponsored bloggers either at the beginning or at the end of the blog posts. Depending on the budget and requirements of a given campaign, each blogger receives compensation (in the form of either money or free products). Bloggers then write and post content on their own blog websites about the campaign; bloggers get paid more if they post something on multiple social media channels.

### 2.3.2 Dependent Variables

*Number of blog post comments.* Every blog post had an option for blog readers to leave comments. Comments of other readers are visible to any subsequent reader of the blog, but other readers do not receive notification when a new comment has been posted. Our primary measure of engagement is the number of comments each blog post received (see Table 3 for constructs, Table 4 for descriptive statistics of the variables, and Table 5 for the correlations).

**Table 3: Constructs**

| Construct | Definition | Operationalization |
|---|---|---|
| Facebook post likes | Primary measure of Facebook engagement is the number of likes each post received. | Count; the total number of likes per blogger per campaign |
| Blog post comments | Primary measure of engagement is the number of blog post comments each blog post received. | Count; the total number of comments per blog post, blogger, and campaign |
| Facebook posts | Number of Facebook posts per blogger per campaign | Count; control variable |
| Followers | Represents blogger's social media presence and is also an indication of blogger strength | Quantitative; the average number of twitter and Facebook followers that a blogger has in online network |
| Awareness campaign | Increases brand awareness and spreads information to consumers; occurs at an early stage in the purchase funnel because consumers are not yet trying to evaluate whether to purchase the product. | Categorical; campaign intent is focused on raising awareness about a specific brand |
| Trial campaign | Encourages consumers to make a purchase; typically linked to actions required of consumers (e.g., purchase) | Categorical; campaign intent is focused on increasing purchase or trial behavior |
| Expertise | Is indicative of how bloggers portray themselves as a source of information as a sponsored blogger | Quantitative; a sum of the person's educational affiliation and blogger credentials. Range: 0–2 |
| Functional | Functional value captures the believability and informativeness of a post. | Quantitative; a factor score of content that is genuine/sincere, honest, informative, pleasant, relatable, understandable, believable, and relevant, as well as usage consideration |
| Hedonic | Hedonic value of a post refers to the enjoyment, emotions, and entertainment a consumer experiences from reading a post. | Quantitative; a factor score of content that is attention getting, creative, emotional, energetic, humorous, memorable, strong, unique, and warmhearted |
| Giveaways | Marketing actions designed to generate specific responses and engagement from consumers. | Categorical; campaign-level variable, whether or not a giveaway was included as part of the campaign |

**Table 4: Descriptive Statistics**

| Variable | N | M | SD |
|---|---|---|---|
| Number of Facebook post likes | 1,398 | 17.53 | 100.64 |
| Number of Blog post comments | 1,826 | 21.23 | 70.02 |
| Average number of followers | 1,267 | 21,246.10 | 24,812.43 |
| Weekend post | 1,830 | 14.8%* | 0.4 |
| Type of campaign: awareness | 1,830 | 35.1%* | 0.48 |
| Type of campaign: trial | 1,830 | 64.9%* | 0.48 |
| Expertise (sum of credentials and education) | 1,816 | 0.36 | 0.63 |
| Blogger travel/foodie | 1,816 | 0 | 1 |
| Blogger persona | 1,816 | 0 | 1 |
| Blogger lifestyle | 1,816 | 0 | 1 |
| Blogger values | 1,816 | 0 | 1 |
| Functional value of post | 1,830 | 0 | 1 |
| Hedonic value of post | 1,830 | 0 | 1 |
| Giveaway | 1,825 | 25.5%* | 0.44 |
| Inverse Mills ratio | 1,819 | 0.27 | 0.18 |

*Percentage of occurrences

## Table 5: Variable Correlations

| Variable | Number of Facebook post likes | Number of blog post comments | Avg. no. of followers | Functional value | Hedonic value | Weekend post | Blogger expertise | Blogger persona | Blogger travel/foodie | Blogger lifestyle | Blogger values | Campaign intent | Giveaway |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Number of Facebook post likes** | 1.0000 | | | | | | | | | | | | |
| **Number of blog post comments** | 0.0028 | 1.0000 | | | | | | | | | | | |
| **Avg. no. of followers** | 0.0775* | 0.0067 | 1.0000 | | | | | | | | | | |
| **Functional value** | 0.0209 | -0.0270 | 0.1124* | 1.0000 | | | | | | | | | |
| **Hedonic value** | -0.0297 | -0.0491* | -0.0771* | 0.0000 | 1.0000 | | | | | | | | |
| **Weekend post** | 0.1082* | -0.0382 | 0.0480 | -0.0194 | 0.0114 | 1.0000 | | | | | | | |
| **Blogger expertise** | -0.0688* | 0.1579* | -0.01122 | -0.0280 | 0.0468 | -0.0088 | 1.0000 | | | | | | |
| **Blogger persona** | 0.0130 | 0.0004 | 0.1244* | -0.0213 | -0.0242 | -0.0001 | 0.1659* | 1.0000 | | | | | |
| **Blogger travel/foodie** | -0.0077 | 0.0394 | 0.2450* | 0.0467* | -0.0300 | 0.0318 | -0.00243 | 0.0000 | 1.0000 | | | | |
| **Blogger lifestyle** | -0.0103 | 0.0191 | -0.1018* | -0.0099 | -0.0036 | 0.0109 | 0.03957 | 0.0000 | 0.0000 | 1.0000 | | | |
| **Blogger values** | -0.0108 | -0.0017 | -0.0990* | -0.0021 | -0.0049 | -0.0213 | 0.01375 | 0.0000 | 0.0000 | 0.0000 | 1.0000 | | |
| **Campaign intent** | 0.1550* | -0.0981* | 0.0283 | 0.0792* | -0.0290 | 0.02302 | -0.2050* | 0.0314 | 0.0084 | 0.0169 | 0.0261 | 1.0000 | |
| **Giveaway** | -0.0432 | 0.2873* | -0.0242 | -0.0608* | -0.0062 | -0.0166 | 0.0508* | 0.0992* | 0.0087 | 0.0342 | -0.0586* | -0.0531* | 1.0000 |

*Significant at $p < .05$.

Notes: The unit of analysis is the blog post.

*Number of Facebook post likes.* Bloggers frequently used their social media outlets to post about different blog campaigns. Facebook followers of a blogger can see the new post in their Facebook news feed, while others need to seek out the post directly from the blogger's Facebook profile. To measure Facebook engagement, we counted the number of Facebook post likes.

### 2.3.3 Independent Variables

*Campaign intent.* Companies typically divide campaigns into two categories, those designed to raise awareness and those designed to increase trial. In our data set, of the 57 total campaigns, 29 had an awareness intent and 28 had a trial intent. The awareness campaigns focused on increasing brand recognition. For example, an AT&T Mobile School Safety campaign encouraged people to talk to their children about using mobile phones safely. These campaigns were not directly trying to motivate people to make a purchase but instead were focused on building brand awareness. By contrast, the trial campaigns focused on increasing consumer trial for products or services. Examples of this type of campaign included Church Hill Classics' diploma frames and Veritas Genetics' at-home BRCA test.

*Campaign incentives.* We identified campaigns (29%) in terms of whether they included a campaign incentive (i.e., a giveaway). Giveaways typically request that readers like or share a blog post to be entered for a chance to win a prize. For example, Johnson & Johnson's Donate-a-Photo campaign had a giveaway prize of $100 worth of products.

*Blogger average number of followers*. The average number of Twitter and Facebook followers represents a blogger's social media presence and is also an indication of blogger strength. We used bloggers' Twitter and Facebook followers for two reasons: (1) Facebook and

Twitter are two of the largest social media platforms, and (2) the number of followers on the blog web pages themselves are unavailable. We use the natural log of average number of Twitter and Facebook followers in the models to account for the large spread, and we mean-centered them to prevent any issues of collinearity. We also use alternative operationalizations and re-estimate the main model using these measures (for the results, see Appendix A).

*Blogger psychographic profile factors*. First, we pulled the public profiles of each blogger in our data set, as described on their blog pages. Second, three coders (blind to the hypotheses) examined the bloggers' public profiles and listed key themes that captured their psychographic profiles (i.e., interests, activities, and opinions; see Table 6). This procedure revealed 14 main psychographic profile dimensions, dummy coded as 1 if present in the profile and 0 if not. Third, we used factor analysis with varimax rotation to identify overarching characteristics of bloggers. The analysis revealed five blogger characteristics: expertise, travel/foodie, persona, lifestyle, and values (for the rotated factor patterns, see Table 7). Travel/foodie consists of travel and food & wine. Persona reflects professional reference, technology and social media reference, and brand affiliation. Lifestyle comprises homeschooling, an environmental affiliation, and a health affiliation. Finally, values are based on religious and political affiliations.

**Table 6: Blogger Profile Coding**

| Coding Category | Example Keywords |
|---|---|
| Religious | - “…who loves Jesus”<br>- “Follower of Jesus”<br>- “Religion” |
| Professional | - “Dental hygienist”<br>- “Nurse”<br>- “Paralegal” |
| Blogger credential listed | - “Social Media Consultant”<br>- “Nielsen 50 Power Mom”<br>- “Online content professional” |
| Homeschooling advocate | - “Hybrid homeschooler”<br>- “Homeschooling Mom of 6” |
| Travel acknowledgment | - “Travel”<br>- “Explorer at Heart” |
| Special needs advocate | - “Special needs advocate”<br>- “Down syndrome advocate” |
| Technology/social media | - “Twitter party host”<br>- “Pinterest addict” |
| Location reference | - “Chicago”<br>- “Texas Type A Mom”<br>- “Los Angeles based bilingual food writer” |
| Political affiliation | - “Democrat”<br>- “Liberal”<br>- “Republican” |
| Educational affiliation | - “Ivy League Graduate”<br>- “University”<br>- “B.A.” |
| Brand affiliation | - Brand<br>- Brand name<br>- Product |
| Food & wine affiliation | - Food<br>- Wine<br>- Foodie |
| Environmental affiliation | - Organic<br>- Green<br>- Natural |
| Health affiliation | - Healthy<br>- Fitness |

**Table 7: Varimax Factor Rotation for Blogger Psychographic Variables**

| Psychographic Variables | Expertise | Travel/Foodie | Persona | Lifestyle | Values |
|---|---|---|---|---|---|
| Religious | -0.13 | -0.32 | -0.03 | 0.22 | **0.65** |
| Professional reference | -0.18 | -0.23 | **0.71** | 0.07 | -0.03 |
| Blogger credential | **0.71** | 0.02 | 0.19 | 0.00 | -0.01 |
| Homeschool | 0.16 | -0.03 | -0.06 | **0.48** | 0.22 |
| Travel | -0.02 | **0.72** | 0.14 | -0.03 | -0.04 |
| Special needs | -0.15 | 0.00 | -0.01 | 0.07 | 0.12 |
| Technology/social media | 0.27 | 0.36 | **0.49** | -0.07 | 0.17 |
| Location reference | -0.67 | 0.17 | 0.21 | -0.10 | 0.06 |
| Political affiliation | 0.04 | 0.14 | -0.04 | -0.17 | **0.72** |
| Educational affiliation | **0.71** | 0.01 | 0.09 | 0.08 | 0.05 |
| Brand affiliation | 0.16 | 0.07 | **0.66** | -0.01 | -0.11 |
| Food & wine | -0.11 | **0.76** | -0.20 | 0.07 | -0.01 |
| Environmental affiliation | 0.07 | -0.15 | -0.05 | **0.60** | -0.23 |
| Health affiliation | -0.18 | 0.26 | 0.19 | **0.67** | 0.04 |

*Blogger expertise.* We measure blogger expertise by the presence of the person's educational affiliation and blogger credentials in his or her profile. Prior research has also used blogger profiles to manipulate source (Uribe, Buzeta, and Velásquez 2016). An educational affiliation includes reference to a specific higher education degree (e.g., "Bachelor of Arts"), while blogger credentials refer specifically to status as a credible blogger (e.g., "social media consultant," "Nielsen 50 Power Mom"). Blogger expertise, which ranges from 0 to 2, is the sum of the two measures.

***Post Variables***

*Weekend post.* Weekend post is an indicator variable for whether the post occurred on a weekend, coded as 1, or a weekday, coded as 0. We used this to capture weekend versus weekday seasonality. Hamilton, Schlosser, and Chen (2017) find that the time of day that the content is posted influencers when people subsequently discuss it. We incorporate this as a control variable for the temporal element.

*Number of Facebook posts.* The number of Facebook posts serves as a control variable. For sponsored blogging campaigns, bloggers will post on blogs and then post on Facebook linking to the blog post. To control for the number of Facebook posts, we include this as a variable in the model.

*Hedonic and informational value associated with the blog post.* Three coders classified the hedonic and informational value associated with a given blog post; we prequalified the coders to match the demographics of the bloggers' audiences. We based our measures on Yuvaraju, Subramanyam, and Rao (2014), who develop a 20-item emotion scale for advertisements. We used coders from Amazon Mechanical Turk to measure various aspects of sentiment on a seven-point scale (1 = "not at all," 7 = "extremely"), including how much the blog posting was attention getting, boring, creative, emotional, energetic, genuine/sincere, honest, humorous, informative, irritating, memorable, pleasant, strong, unique, warmhearted, relatable, understandable, believable, and relevant. We selected coders who were as similar to the blog audience as possible (i.e., they were also mothers with a child under 18 years in the household). We solicited three coders for each blog post and asked them to code only a subset of blog posts (typically three posts each), suggesting that there are variations introduced across different blog posts due to the varying identities of coders.

First, to measure the agreement between coders and calculate a more accurate alpha score, we used the methodology Shrout and Fleiss (1979) describe. Shrout and Fleiss's reliability measure helps us compute the reliability of $n$ targets across $k$ coders, with the coders being treated as random (vs. fixed) effects. Shrout and Fleiss specify six correlations for this measure, and we use ICC(1,1), which is appropriate when subjects have the same number of coders, each item is rated by multiple coders, and coders are randomly assigned. Computing this ICC yields a

Shrout–Fleiss single ICC score agreement of .998, which is considered quite high (see Koo and Li 2016). As a second approach to assess reliability, we estimated a standardized alpha within three coders for each sentiment value for each blog post, to account for the different coders on each post. We then averaged these standardized alphas and obtained an average reliability of .51 and a median reliability of .56.

Each blog post was coded for a variety of sentiment variables, some of which may be correlated. To reduce the dimensionality of the data and increase parsimony, we conducted a factor analysis. Factor analysis with a varimax rotation revealed two factors with eigenvalues greater than 1 (for factor loadings, see Table 8, which we labeled as "functional value" and "hedonic value." The variables that loaded most highly on perceived functional value were genuine/sincere, honest, informative, pleasant, relatable, understandable, believable, relevant, and benefits believable. The variables that loaded most highly on perceived hedonic value were attention getting, creative, emotional, energetic, humorous, memorable, strong, unique, and warmhearted.

**Table 8: Varimax Factor Pattern Rotation for Blog Post Sentiment Variables**

| | **Factor 1** | **Factor 2** |
|---|---|---|
| **Sentiment Variables** | **Functional** | **Hedonic** |
| Attention getting | .44 | **.66** |
| Boring | -.47 | -.51 |
| Creative | .33 | **.78** |
| Emotional | .17 | **.71** |
| Energetic | .35 | **.70** |
| Genuine/sincere | **.69** | .49 |
| Honest | **.73** | .43 |
| Humorous | -.08 | **.68** |
| Informative | **.66** | .34 |
| Irritating | -.65 | -.17 |
| Memorable | .37 | **.76** |
| Pleasant | **.61** | .56 |
| Strong | .37 | **.74** |
| Unique | .28 | **.79** |
| Warmhearted | .53 | **.64** |
| Relatable | **.66** | .48 |
| Understandable | **.75** | .07 |
| Believable | **.84** | .17 |
| Relevant | **.67** | .27 |
| Benefits believable | **.85** | .18 |
| Consider using | **.68** | .37 |

### 2.3.4 Selection Model

Because bloggers are chosen to participate in campaigns, selection bias may occur. There are aspects of blogger selection determined by the firm and blogger that we are unable to observe, i.e. prior relationships between the firm and blogger. In order to implement the Heckman selection model, we require an excluded variable that fulfills the following requirements: (1) relevance criterion – our excluded variable must be correlated to the endogenous variable, i.e. blogger selection for a campaign, and (2) exclusion restriction criterion – our excluded variable must not be correlated to the shock in the post engagement variables (Kanuri, Chen, Sridhar 2018). To address this endogeneity issue, we implemented a Heckman (1979) selection model.

The first-stage model used a Probit regression to predict a blogger's selection for a campaign. The variable providing the exclusion restriction for the Stage 1 Probit model is blogger selection of the target's most similar blogger.

The blogger who co-occurred with the target blogger most often is considered the *most similar blogger*. We selected the blogger that occurred most often with the target blogger and used his or her selection for a campaign as an independent variable in the Stage 1 Probit. For example, consider our target blogger Megan who co-occurred in three campaigns with blogger Shannon. We use whether or not Shannon was selected to participate in the campaign of interest to predict whether Megan will be selected for a campaign.

**Table 9: Example of Target and Most Similar Blogger Selection by Campaign**

| Campaign | Target Blogger Selection | Most Similar Blogger Selection |
|---|---|---|
| Barnes & Noble | 1 | 1 |
| Listerine | 1 | 1 |
| Hello Fresh | 1 | 1 |
| OshKosh B'gosh | 0 | 1 |
| ⋮ | ⋮ | ⋮ |
| Walmart | 1 | 0 |

The most similar blogger's selection fulfills the relevance criterion because the selection method of choosing bloggers will be consistent within a campaign, and because the bloggers will share similar unobservable characteristics. By using a blogger most similar to the target blogger, we are able to account for these potential unobservable variables. In addition, selection of the most similar blogger fulfills the exclusion criterion because the selection of a similar blogger will not be directly related to the engagement generated by the focal blogger. Each blogger is acting independently within the campaign, and therefore the engagement captured will be only reflective of the target blogger's actions.

To determine the blogger that is most similar to the target blogger, we created a blogger-by-campaign matrix:

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & v_{ij} \ddots & \vdots \\ v_{n1} & \cdots & v_{nm} \end{bmatrix},$$

where *n* is the number of bloggers, *m* is the number of campaigns, and $v_{ij}$ is the selection for blogger *i* in campaign *j*, such that:

$$v_{ij} = \begin{cases} 1, & \text{if blogger } i \text{ was selected for campaign } j \\ 0, & \text{if blogger } i \text{ was not selected for campaign } j \end{cases}$$

We multiplied this matrix, V, by its transpose to create a blogger-by-blogger matrix, which showed which bloggers co-occurred most frequently:

$$W = \mathrm{VV}^T,$$

where V is the blogger-by-campaign matrix, $V^T$ is the campaign-by-blogger matrix, and W is the blogger-by-blogger matrix:

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & w_{ik} \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix},$$

where $w_{ik}$ is the number of times blogger *i* and blogger *k* co-occurred, i.e. participated in the same campaign.

Industry practice is to match bloggers with common interests in and similarity to the focal campaign. In line with this method, we additionally use the bloggers' profile descriptions and employed varimax factor rotation to create a psychographic index score using the psychographic categories which are not directly related to the outcome of engagement: travel/foodie, persona, lifestyle, and values. Therefore, the Stage 1 Probit model is estimated as:

$$selection_{ij} = \alpha_0 + \alpha_1\left(similar\ blogger\ selection_{ij}\right) + \alpha_2(travel/foodie) + \alpha_3(persona) + \alpha_4(lifestyle) + \alpha_5(values),$$

where the $selection_{ij}$ is a binary variable indicating if blogger *i* was selected to participate in campaign *j*. We then computed an inverse Mills ratio from this selection model and included it in the stage 2 negative binomial regression model to account for selection bias.

Table 10 provides the results of the Stage 1 Probit model. We find that the intercept (b = –2.2744, $p < .01$), similar blogger selection (b = 1.5550, $p < .01$), and the travel/foodie blogger psychographic (b = .0374, $p < .01$) are significant for selection in the Stage 1 Probit model. The exclusion criterion, similar blogger selection, indicates that when a similar blogger to the target blogger is selected for a campaign, the target blogger is more likely to be selected for the campaign. We then included the inverse Mills ratio from the first stage as an independent variable in all second-stage models. The inverse Mills ratio was not significant in the Facebook post likes (z = –.060, $p = .950$) or blog post comments (z = 1.22, $p = .223$) models.

**Table 10: Stage 1 Probit Selection Model**

| Variable | Total Impressions |
|---|---|
| **Intercept** | -2.2744** |
| | (.0188) |
| **Similar blogger selection** | 1.5550** |
| | (.0283) |
| **Travel/foodie** | .0374** |
| | (.0144) |
| **Persona** | .0113 |
| | (.0146) |
| **Lifestyle** | -.0169 |
| | (.0136) |
| **Values** | .0100 |
| | (.0152) |
| **Model fit** | LR $\chi^2(5) = 3117.20$ |
| | Pseudo-$R^2$ = .255 |

Notes: Standard error are in parentheses.
*Significant at $p < .05$.
**Significant at $p <.01$.

### 2.3.5 Model Choice

The dependent variables of interest, blog post comments and Facebook post likes, are count variables. Therefore, we considered using either a Poisson distribution or a negative binomial distribution for count data. A likelihood ratio test indicated that there was overdispersion in the data for the blog post comments ($\chi^2 = 6{,}231$, $p < .001$) and Facebook post likes ($\chi^2 = 31{,}000$, $p < .001$) models. Thus, we used a negative binomial model instead of a Poisson model. In addition, we find no correlation between the error terms of the two models. The second-stage model equations are as follows:

ln(Blog post comments$_i$) =
$\beta_0$ + $\beta_1$(*ln[average number of followers]*) + $\beta_2$(*weekend post*) + $\beta_3$(*campaign intent [awareness vs. trial]*) + $\beta_4$(*blogger expertise*) + $\beta_5$(*functional value of post*) + $\beta_6$(*hedonic value of post*) + $\beta_7$(*giveaway*) + $\beta_8$(*awareness campaign*)(*ln[average number of followers]*) + $\beta_9$(*awareness campaign*)(*functional value of post*) + $\beta_{10}$(*awareness campaign*)(*hedonic value of post*) + $\beta_{11}$(*awareness campaign*)(*blogger expertise*) + $\beta_{12}$(*awareness campaign*)(*giveaway*) + $\beta_{13}$(*inverse Mills ratio*) + $\epsilon_i$.

ln(Facebook post likes$_i$) =
$\beta_0$ + $\beta_1$(*ln[average number of followers]*) + $\beta_2$(*weekend post*) + $\beta_3$(*number of Facebook posts*) + $\beta_4$(*campaign intent [awareness vs. trial]*) + $\beta_5$(*blogger expertise*) + $\beta_6$(*functional value of post*) + $\beta_7$(*hedonic value of post*) + $\beta_8$(*giveaway*) + $\beta_9$(*awareness campaign*)(*ln[average number of followers]*) + $\beta_{10}$(*awareness campaign*)(*functional value of post*) + $\beta_{11}$(*awareness campaign*)(*hedonic value of post*) + $\beta_{12}$(*awareness campaign*)(*blogger expertise*) + $\beta_{13}$(*awareness campaign*)(*giveaway*) + $\beta_{14}$(*inverse Mills ratio*) + $\epsilon_i$.

### 2.3.6 Model Results

Before we describe our full model results (see Table 11), several main effects results are worth noting. In the main-effects-only model (see Appendix), we find that campaign intent exerts a differential main effect on each platform, with awareness intent being more effective for Facebook and trial intent being more effective for blogs. We conjecture that on Facebook because of its lower commercial intent, an awareness campaign is potentially more readily shared among peers in an organic fashion. The nature of campaign incentives (i.e., giveaways) is to encourage participation with specific tasks. The negative impact of incentives on Facebook and the positive impact on the blog platform highlight the potential cannibalizing effect of one social media platform on another.

*Blog post comments model.* Table 11 reports the results of the second-stage model with blog post comments as the dependent variable (N = 1,237). The Akaike information criterion (AIC) for this model was 6,663, the Bayesian information criterion (BIC) was 6,740, and the likelihood ratio test was significant ($\chi^2(13) = 100.64$, $p < .01$). Variance inflation factors (VIFs) were all below 1.09, with an average VIF of 1.04, indicating no issues with collinearity. We found a significant main effect of our control variable, average number of followers (b = .3514, $p < .01$), indicating that this factor significantly drives the number of blog post comments.

**Table 11: Model Results**

| Variable | Blog Post Comments | Facebook Post Likes |
|---|---|---|
| Intercept | 2.0403** | 1.4032** |
| | (.1479) | (.1968) |
| Average number of followers (ln, mean-centered) | .3514** | .2055* |
| | (.0821) | (.0941) |
| Weekend post | -.1837 | .7038** |
| | (.1641) | (.2168) |
| Number of Facebook posts | N/A | .5728** |
| | N/A | (.0891) |
| Campaign intent – awareness | -.2351+ | .7416** |
| | (.1417) | (.1883) |
| Blogger expertise (sum of credentials and education) | -.1228 | .0253 |
| | (.2000) | (.2591) |
| Functional value of post | .0298 | .0520 |
| | (.0790) | (.0906) |
| Hedonic value of post | .2616** | .2215* |
| | (.0888) | (.1007) |
| Giveaway | .4526* | -.7840** |
| | (.1834) | (.2245) |
| Awareness × expertise | .7283* | -.4534 |
| | (.2911) | (.3393) |
| Awareness × functional | -.1269 | -.1533 |
| | (.1185) | (.1308) |
| Awareness × hedonic | -.2167 | -.4824** |
| | (.1323) | (.1356) |
| Awareness × giveaway | .4322 | .5312 |
| | (.3020) | (.3364) |
| Awareness × followers | -.1413 | .1457 |
| | (.1127) | (.1301) |
| Inverse Mills ratio | -.1255 | .1255 |
| | (.3601) | (.4343) |
| Overdispersion (α) | 4.0632** | 3.7449** |
| | (.1915) | (.1829) |
| AIC | 6662.87 | 5581.87 |
| BIC | 6739.68 | 5505.78 |
| –2 Log-likelihood $\chi^2$ | 100.64** | 221.91** |

The main effect of campaign intent (awareness vs. trial) was marginally significant in the blog post comments model (b = –.2351, $p < .10$), while the main effect of blogger expertise was not significant in the final model incorporating interaction effects (b = –.1228, n.s.), which does not support $H_1$. The interaction between type of campaign (awareness vs. trial) and blogger expertise was positive in the blog post comments model (b = .7283, $p = .01$). Further investigation of the interaction effect reveals that the simple slope for high blogger expertise was significant ($p < .05$), indicating that the impact of high blogger expertise varies by campaign intent, in support of $H_{2a}$. The simple slope for low blogger expertise was marginally significant (p=.10), suggesting no differences in effectiveness of low-expertise bloggers across awareness and trial campaigns; thus, $H_{2b}$ is not supported (or receives weak support at p=.10). Figure 2 summarizes the pattern of effects for the interaction between campaign type and blogger expertise. Perceived functional value of the post was not statistically significant, but the hedonic value of the post had a significant impact on the number of blog post comments (b = .2616, $p < .01$), in support of $H_3$. Campaigns that included campaign incentives also significantly increased the number of blog post comments (b = .4526, $p = .01$), in support of $H_4$.

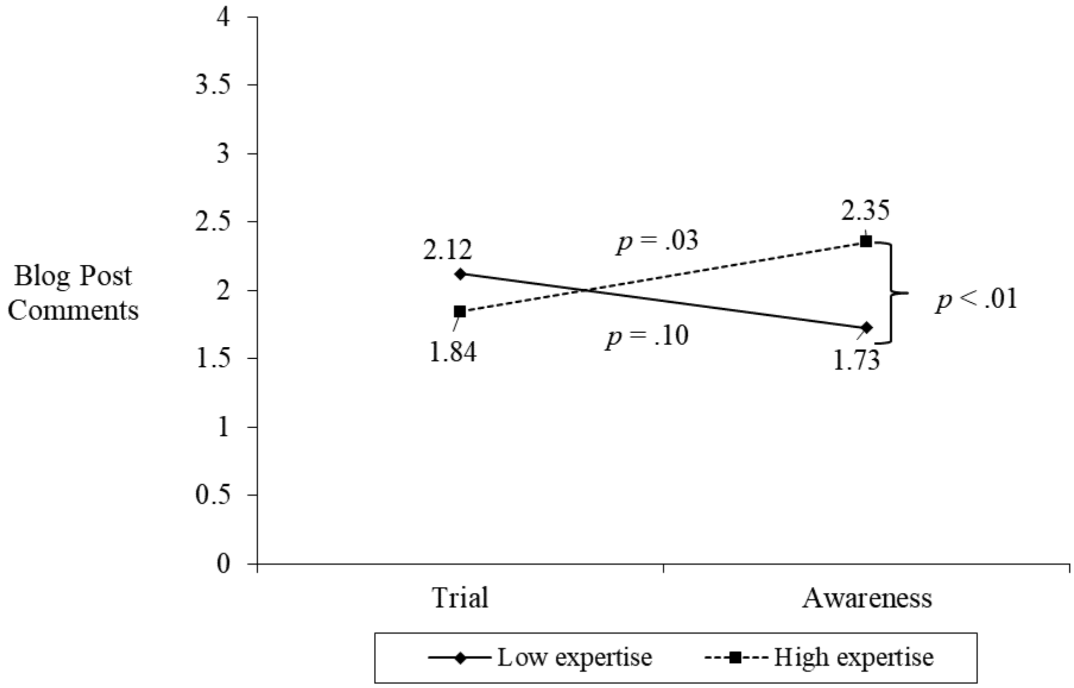



**Figure 2: Blogger Expertise and Campaign Intent on Blog Engagement (Study 1)**

The results indicate that high blogger expertise is beneficial when paired with awareness campaigns but has a lesser effect in the case of trial campaigns. While we initially hypothesized that for low-expertise bloggers, there would be more engagement under trial than awareness intent, we find no evidence of this relationship. We find that hedonic content is positively associated with an increase in blog post comments. We return to this point in the "Discussion" section.

*Facebook post likes model.* Table 11 also reports the results of the second-stage model with Facebook post likes as the dependent variable. The AIC for this model was 5,508, the BIC was 5,582, and the likelihood ratio test was significant ($\chi^2(14) = 221.91$, $p < .01$). The VIFs were all below 1.06, with an average VIF of 1.04, indicating no issues with collinearity. The number of Facebook posts was significant (b = .5728, $p < .01$). We found a significant main effect of the average number of followers (b = .2055, $p < .05$), indicating that this drives Facebook post likes.

Campaigns that included giveaways also significantly decreased the number of Facebook post likes (b = –.7840, $p < .01$).

Blogger expertise was not significantly related to the number of Facebook post likes (b = .0253, n.s.); however, we found a significant main effect of hedonic value (b = .2215, $p = .03$), in support of $H_5$. The main effect of campaign intent (awareness vs. trial) was significant in the Facebook post likes model (b = .7416, $p < .01$), in support of $H_6$. There was a significant, negative interaction effect of campaign intent and hedonic value (b = –.4824, $p < .01$). In light of the positive main effects of hedonic value and awareness campaigns, the negative interaction term implies that hedonic value is positively related to Facebook post likes for trial campaigns and negatively related to Facebook post likes for awareness campaigns, providing support for $H_7$. Figure 3, which plots the pattern of results, shows that posts low in hedonic value can weaken engagement, particularly for trial campaigns. Taken together, the results indicate that multiple factors can increase engagement in sponsored Facebook posts. Regarding the control variables, having more Facebook posts, posts on weekends, and a higher number of followers are all related to an increased number of Facebook post likes. Posts lower in hedonic content are particularly harmful when paired with trial campaigns on Facebook.

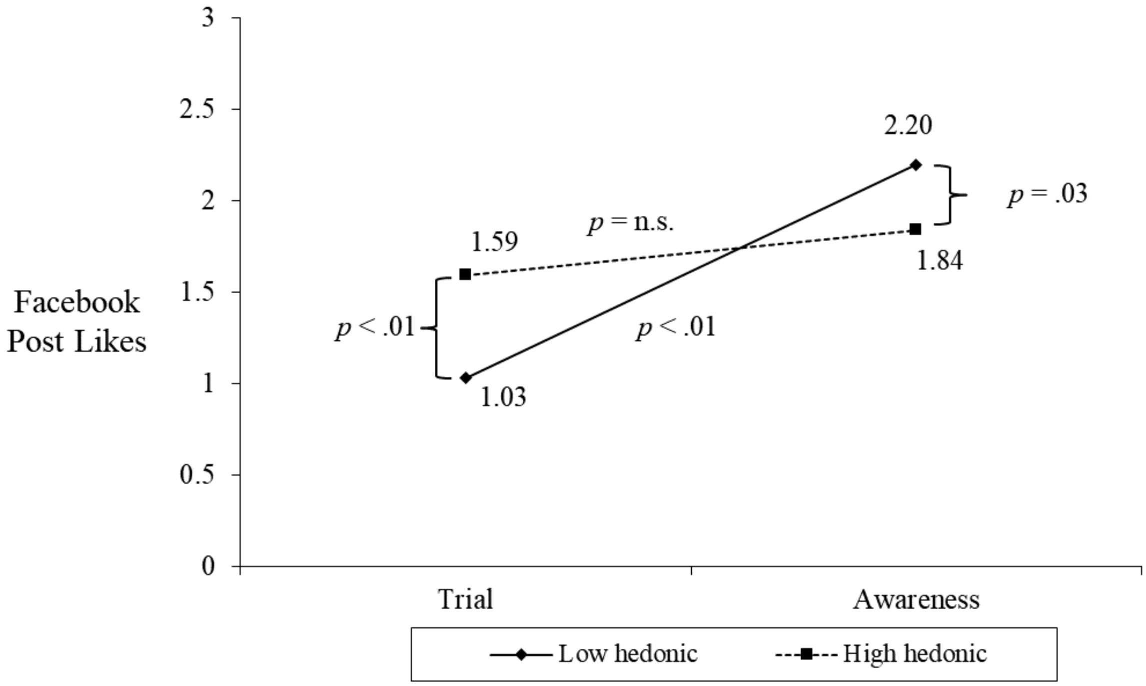



**Figure 3: Hedonic Content and Campaign Intent on Facebook Engagement (Study 1)**

We find that the blog platform and Facebook platform exhibit differences in drivers of engagement. Campaign incentives negatively affect the Facebook platform but not the blog platform; we conjecture that this is due to the cannibalizing effect of the blogging platform. Timing of the posts (weekends vs. weekdays) also positively affects Facebook, but this effect is not consistent for the blog platform model.

### 2.3.7 Discussion

In this study, we evaluated the effectiveness of influencer marketing campaigns using an empirical database of sponsored bloggers. Taken together, the results provide support for most of our hypothesized effects (which the exception of $H_1$ and $H_{2b}$, which were not supported). Across both models, we find a positive impact of the number of followers. Controlling for the number of followers, we find that blogger expertise, campaign intent, hedonic value, and interactions among these variables influence engagement on blog and Facebook platforms. We also find differences in the success drivers of sponsored blogging campaigns across the platforms. High blogger expertise interacts with campaign intent in the blog platform but not the Facebook platform.

We find a significant interaction between campaign intent and hedonic value on Facebook platforms. Specifically, our findings indicated that hedonic value exerts a greater impact in trial campaigns, which supports the explanation that hedonic content may provide a reason for Facebook users to share information or like a blog post with an overt commercial intent, confirming the compensatory role of hedonic value in mitigating the negative effect of a less desired post. In addition, we found a negative effect of campaign incentives on Facebook post likes for both awareness and trial campaigns, potentially due to cross-platform cannibalization of the Facebook platform, by the blogging platform. Campaign incentives may cause participants to interact with a blog post more directly in the blogging environment, even though they may have first encountered the information on Facebook.

In addition, we estimated a series of alternative models for robustness checks, including examining when posts are cross-posted on Facebook and blogs, alternative measures of content sentiment, alternative specifications of number of followers, varying measures of post engagement, and alternative coding for the varimax factor rotations. The robustness checks also included another version of the Stage 1 Probit model specification, models using Gaussian Copula, and fixed effects negative binomial models. The results of these alternative specifications are consistent with our reported findings (for details, see Appendix A).

Our results thus far have been based on data collected from a real-world context (actual campaigns featuring sponsored bloggers), providing high generalization and meaningful insights into the complex interplay of multiple factors that influence how these campaigns actually function in real life. However, field data limit our ability to manipulate key independent variables, creating the possibility that extraneous variables could account for the effects. To account for this possibility and improve our ability to draw meaningful conclusions from this research, we aimed to replicate our findings in a tightly controlled setting, by experimentally manipulating our key variables. We focused attention on finding additional support for a key interaction effect observed in the blog platform setting, i.e., the interaction between campaign intent and blogger expertise in a blog setting.

## 2.4 Study 2

The purpose of Study 2 is to replicate one of the more counterintuitive results—namely, the blogger expertise × campaign intent interaction on the blog platform—to provide further support for $H_2$. We posit that campaign intent will have a differential impact on purchase likelihood in the case of high-expertise bloggers but will not affect purchase likelihood in the case of low-expertise bloggers.

### 2.4.1 Pretests

*Expertise pretest.* This pretest serves to (1) link blogger profile characteristics with perceived expertise and (2) check the strength of our manipulation of blogger expertise. We kept the sample population as similar to the target audience as possible. Those sampled were women with children under the age of 18 (N = 97). The pretest was a between-subjects design with two expertise levels (high and low). In the high-expertise condition, the participants read the blogger profile: “Mother of 2! I love my hubbie and hiking! Named a Parents Magazine Top Mom in

Digital Media, brand ambassador, Nielsen Power 50 mom, and #ivyleague grad!" In the low-expertise condition, participants read: "Mother of 2! I love my hubbie and hiking! Quirky. Sparkly. Loves bad jokes and good coffee."

To create a robust measure of expertise, we used the items from Ohanian's (1990) scale to measure celebrity endorser expertise. On a scale from 0 ("strongly disagree") to 100 ("strongly agree"), participants rated whether they felt the blogger was expert, experienced, knowledgeable, qualified, and skilled. We averaged these five items together ($\alpha = .96$) to create an overall perceived expertise score.

Because our participants are also mothers, we controlled for potential homophily to rule this out as an alternative explanation of the blogger expertise effects. Therefore, participants rated three items regarding blogger homophily (0 = "strongly disagree," 100 = "strongly agree"): "I feel that the blogger is similar to me," "I feel that the blogger is a peer," and "I feel that the blogger thinks like me." We averaged these three items together to create an overall homophily score ($\alpha = .95$). Controlling for age and homophily, we found that perceived expertise is higher under the high blogger expertise manipulation than the low blogger expertise manipulation ($M_{high} = 62.20$, $M_{low} = 59.37$; $F(3, 93) = 20.13$, $p < .01$). In addition, we found a difference in perceived homophily for high- versus low-expertise bloggers when controlling for age, such that homophily is higher in the case of low-expertise bloggers ($M_{high} = 46.89$, $M_{low} = 60.26$; $F(1, 94) = 7.50$, $p < .01$).

*Campaign pretest.* The goal of this pretest was to further test the manipulation of campaign intent (trial vs. awareness). The sample population included women with children under the age of 18 (N = 164). This pretest was a three condition (campaign intent: awareness, trial, control) between-subjects design. Participants read a sponsored blog post depending on the condition to which they were randomly assigned. In the control condition, participants read an unrelated post about finding the right job. The awareness and trial campaigns were both about an educational mobile game targeted at middle schoolers. The posts were identical, except that the trial campaign had an additional message at the bottom that read “BUY NOW!!!”

We measured persuasion knowledge using scale items from Ahluwalia and Burnkrant (2004). Participants rated the author of the blog post on a nine-point bipolar scale for three items: good/bad, not pushy/pushy, and not aggressive/aggressive. We averaged these items to create a persuasion knowledge measure for the source ($\alpha = .85$). Controlling for age, we found a significant difference in perception of the source based on the campaign intent manipulation ($M_{awareness} = 3.38$, $M_{trial} = 4.27$, $M_{control} = 3.35$; $F(3, 160) = 2.81$, $p < .05$). Using planned pairwise contrasts, we found a significant difference in persuasion knowledge between the trial and awareness campaigns ($p < .05$) and between the trial and control campaigns ($p < .05$). This indicates that persuasion knowledge is higher in trial campaigns than in either the awareness or control campaign conditions.

### 2.4.2 Method and Results

This experiment was a 2 (expertise: high, low) × 2 (campaign: awareness, trial) between-subjects design. The sample came from a Qualtrics panel of mothers (N = 395). Our context for this study is an educational paid app (Water Bears) targeted at middle schoolers (and their parents), designed to improve spatial reasoning. Participants read identical sponsored blog postings about Water Bears (similar to what was used in the pretest). In the trial condition, an additional phrase at the bottom stated: “BUY NOW!!!” The expertise conditions were identical to those in the pretest. Participants rated how likely they would be to purchase the Water Bears app on a scale from 0% (“not likely at all”) to 100% (“very likely”).

We analyzed the data using analysis of variance containing all the main effects (i.e., blogger expertise, campaign intent, and their interaction). The overall model was significant ($F(7, 387) = 22.29$, $p < .01$). The main effect of expertise was not significant ($F(1, 387) = 0.95$, $p = .33$), but the main effect of campaign intent was significant ($F(1, 387) = 8.56$, $p < .01$). In support of our hypothesized effect, the interaction between expertise and campaign intent was also significant ($F(1, 387) = 8.88$, $p < .01$). We controlled for age, homophily, whether participants had children in middle school, and whether they follow sponsored bloggers online. After controlling for these variables, the test of simple slopes indicated that, consistent with $H_{2a}$, the impact of high blogger expertise on purchase likelihood is higher for awareness campaigns than for trial campaigns ($M_{awareness} = 34.10$, $M_{trial} = 20.66$; $F(1, 387) = 13.32$, $p < .01$). That is, when blogger expertise was high, participants expressed a higher purchase intent for the awareness campaign than the trial campaign. Next, examining purchase likelihood under low blogger expertise, we found no significant difference between awareness and trial campaigns ($M_{awareness} = 30.24$, $M_{trial} = 30.29$; $F(1, 387) = .14$, $p = .7106$), which, consistent with our empirical results, fails to support $H_{2b}$. The impact of a low-expertise endorser on purchase likelihood does not depend on campaign intent. This pattern of findings confirms the findings from our empirical data set (see Figure 4).

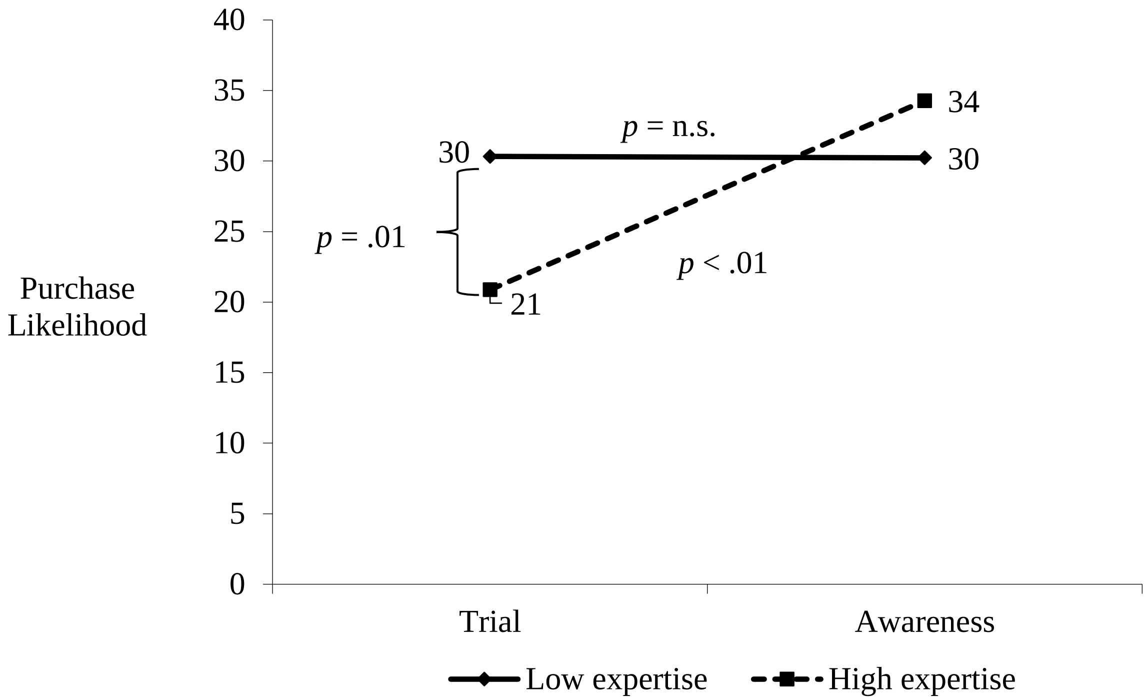



**Figure 4: Blogger Expertise and Campaign Intent Effects on Purchase Likelihood (Study 2)**

***Discussion***

Study 2 provides additional, supplemental evidence for the interaction between source expertise and campaign intent on a blog platform. We show that in the case of high-expertise bloggers, awareness intent yields a higher purchase likelihood than trial intent. By demonstrating this effect using purchase likelihood in an experimental setting, we provide further support for the validity of this finding.

## 2.5 General Discussion

This research sheds light on the key drivers of success of influencer marketing campaigns and offers a novel contribution by examining the interplay of social media platforms and success factors. We find that while network, blogger characteristics, and content characteristics affect multiple types of sponsored blogger engagement, the level of platform involvement and the campaign intent matter for the degree of success, thereby providing broad support for most of our hypotheses. We use both field data based on a large data set of influencer marketing campaigns and a controlled experiment to show convergent evidence of majority of the hypothesized effects. By understanding this framework to increase engagement, companies can choose bloggers more effectively, matching their characteristics to campaign goals.

We expect the sponsored blogging results to differ from those for other social media and paid media for two reasons. First, the nature of influencer marketing is distinct from both WOM and traditional advertising because influencers blend elements of paid and earned media. From a motivation perspective, while traditional advertising has a single goal (i.e., to persuade consumers to purchase), influencers display additional loyalty to their followers; they want to help the company, but also need to maintain their credibility as an informed voice. Second, the message is designed and implemented by the influencer, not the company. This is also distinct from traditional advertising and spokesperson marketing tactics, due to bloggers' creative freedom, but it is also distinct from pure organic WOM, because they are being sponsored by the company. With these influencer nuances in mind, we expect that consumers will interpret the message and source differently depending on where and how it is presented to them.

### 2.5.1 Theoretical Contributions

Our key contributions involve understanding the interplay of post content characteristics (i.e., hedonic value of a blog post), source expertise, and campaign characteristics (i.e., campaign intent and incentives in an awareness-building or trial campaign) on campaign intent and social media platform. While campaign intent has received attention in advertising literature (Muller 1983), our study is the first to examine the impact of influencer marketing campaign intent on engagement. We find that campaign intent is an especially pertinent moderator to many of the relationships in our study. For example, we find that campaign intent moderates the relationship between source expertise and blog post engagement. We also find that campaign intent moderates the relationship between hedonic content and Facebook post engagement. These findings suggest that the relationship among source, content, and engagement should not be assessed in isolation from campaign intent.

In addition, we contribute to the literature on blogger expertise by demonstrating conditions in which expertise has (1) a positive impact, (2) a negative impact, and (3) no impact. Specifically, we demonstrate that in some conditions, source expertise is positive, and in others, it is nonsignificant. Expert endorsement is beneficial under an awareness intent, while a novice endorsement is beneficial under a trial intent. This effect holds under high-involvement (lower-distraction) social media platforms. On low-involvement (high-distraction) social media platforms, however, source expertise does not affect engagement. We provide a more nuanced explanation of expertise and its role in online brand engagement. Taken together, these findings provide a richer understanding of source expertise in the case of influencer marketing.

We extend prior research on influencer marketing by highlighting the importance of consumer skepticism differences, which may cause campaign intents (awareness or trial) aimed at different stages of consumer decision making to function differently. At earlier stages of decision making, consumers are open to guidance from those with high perceived expertise. However, closer to trial, consumers are open to endorsements that originate from either less expert (presumably more homophilous) or more expert sources. This difference is only true in high-involvement platform settings such as blogs. Understanding the contextual effects guiding the impact of source expertise in online influencer marketing settings is a key contribution of this research. It extends prior works on influencer marketing settings that focus on either expertise (Uribe, Buzeta, and Velásquez 2016; Zhu and Tan 2007) or stage of consumer decision making (Hudson and Hudson 2013) but do not examine their interplay.

We also argue that the motivations driving people to use social media platforms influence how they view different types of influencer marketing campaigns. In a blog environment, in which users are motivated to process information deeply and to engage with bloggers' information and content, trial campaigns are better received. In a Facebook environment, in which users' motivations are more focused on sharing information with peers, awareness campaigns have a more positive role. Given this general preference for awareness (vs. trial) campaigns on Facebook, hedonic value of a blog post takes on more significance in the context of trial campaigns.

Furthermore, our findings show that post content, in terms of hedonic value, is important in generating post engagement. We extend the findings of Berger and Milkman (2012), who argue that hedonic content increases social transmission and virality of online messages. We find that hedonic value has a significant effect on both blog and Facebook platforms. We also show that on low-involvement (high-distraction) social media platforms, hedonic content can be beneficial when paired with trial campaigns, perhaps due to their overt commercial intent. In awareness-building campaigns, in which user motivations involve sharing of information, hedonic value may be distracting to the primary goal. Thus, hedonic content of online communications is not always beneficial to marketing campaigns.

Our findings are revealing regarding the impact of campaign incentives, which research has previously shown to increase WOM (Berger and Schwartz 2011) and enhance quality perceptions of a product (White 2013). We demonstrate that incentives (a *chance* to win a giveaway) generate WOM benefits in the form of increased engagement (i.e., blog post comments). This finding advances the literature by showing that increased WOM and engagement can be generated without giving a free product to every person; simply offering a chance to be the recipient is enough to induce the benefits of free products. This greatly reduces the costs associated with running a campaign with free product incentives, while still generating a similar response.

One potential rationale for why giveaways have a positive effect in blog environment but a negative effect in the Facebook post models is because giveaways are typically executed on the blog platform setting, and blogs are cannibalizing Facebook engagement. An alternative explanation, which could be the focus of future research is that high involvement platforms in general are more conducive to driving engagement using free goods and incentives. Prior research suggests that when consumers are more involved, they want to minimize risk through information-search in their decision-making process (Delgado-Ballester and Munuera-Aleman 2001). This free product, or incentive, could be seen as a way to lower the risk of a new purchase. This is worth examining in the context of a broader understanding of customer engagement.

This article offers a unique contribution by examining the differences between social media platforms. While we empirically focused on blogs and Facebook, the findings can be extended to other social media platforms that may be created in the future. As platforms continue to develop, the extent of involvement generated by a platform can help inform decisions on influencer marketing strategies.

The focus of this research is on online engagement, which sheds more light on customer profitability than a mere focus on customer attitudes or preferences. Furthermore, our examination of cross-platform impacts (i.e., blogs and Facebook) dovetails with other research examining how different advertising media may synergistically improve customer engagement and profitability. Kireyev, Pauwels, and Gupta (2016) investigate the dynamic interaction between paid search and display ads. We extend these findings by focusing on one form of social media marketing that straddles the earned and paid social media types. Therefore, our findings are of particular relevance in light of the increased blurring between these two types of social media marketing. The variations observed across social media platforms indicate that type of platform can affect the profitability of digital marketing expenditures.

### 2.5.2 Managerial Implications

We offer novel insights to managers implementing influencer marketing campaigns. First, this article delineates best practices for sponsored bloggers based on marketing campaign intent and platform. When trying to bolster awareness campaigns on a blogging platform, managers should feature the expertise and credibility of the blogger. However, in the case of trial campaign intent, campaigns by both expert and novice sources will be equally successful.

Second, when implementing campaigns on Facebook or any other high-distraction platform, managers should vary content strategy depending on campaign intent. Trial campaigns can benefit from featuring posts with high hedonic value, particularly in high-distraction environments such as Facebook. Furthermore, when choosing bloggers to implement a strategy involving multiple high-distraction platforms, managers should focus on selecting bloggers with a large follower base to ensure the highest penetration and engagement.

Third, with regard to the impact of campaign intent on outcomes, we recommend that managers use the appropriate drivers of success for blog engagement (i.e., blogger expertise, campaign incentives) in awareness campaigns and rely on hedonic-valued content on blog platforms. We further recommend that managers avoid using campaign incentives on Facebook or other low-involvement, high-distraction platforms, such as Twitter or Instagram, and instead focus on the hedonic value of post content.

### 2.5.3 Limitations and Future Research Directions

This research is subject to certain limitations, which may present new directions for further research. We explored only a limited set of outcome metrics associated with a particular blog post and did not directly test for the impact on return on investment (ROI). However, Kumar et al. (2013) show that both social media and customer WOM increase ROI, and Kumar and Pansari (2016) demonstrate the relationship between engagement and ROI. Further research could increase the set of outcome measures of a given campaign by considering the direct impact of a blog posting on consequential outcomes, such as sales and ROI. Further examination of why customer engagement could impact these performance outcomes is worth examining, thereby extending the framework proposed by Harmeling et al. (2017). Our measurement of key constructs, such as sentiment, relied on post hoc measures based on judges evaluating each blog posting for factors such as creativity/uniqueness and personal relevancy. A more direct measure would involve having the audiences of a given blogger rate his or her posts for various aspects of sentiment. In addition, research could also include a field experiment of the blogger choice informed by this research versus the current methods for selecting bloggers for campaigns.

In general, sponsored blogging and influencer marketing have been the target of ethical debates in recent years. Some critics argue that social influencers fail to reveal their sponsorship by companies, thereby creating a perception that their sponsored posts are organic WOM. This type of deceptive marketing practice has been at the heart of various Federal Trade Commission investigations of Instagram posts in recent years (Ingram and Bartz 2017). The Federal Trade Commission (2017) has reached out to influencers directly and reiterated its requirements to disclose clearly any endorser and advertiser connection. As noted previously, all sponsored posts in the current research included a declaration of sponsorship at the beginning of the blog post. Still, there is room for research on how sponsored blogging as an advertising medium is distinct from other forms of advertising that consumers view unambiguously as paid advertising.

# 3.0 ESSAY 2: IS THE FOLLOWER THE LEADER? HOW THE FIRST FOLLOWER ESTABLISHES THE GROUP NORM IN SEQUENTIAL BEHAVIOR

Sequential behavior is a phenomenon that can be seen everywhere - from ordering at restaurants or bars with friends, to posting comments on internet threads with strangers. Sequential behavior can be seen in the formation of trends and movements and coming to a unanimous decision in a jury. The variety of contexts in which sequential behavior exists offers a unique research area. Consider a scenario where you and your friends are at happy hour and ordering drinks. In one situation, the first person orders a beer, and then the second person also orders a beer. In another situation, the first person still orders a beer, but the second member orders a mixed drink. How does the rest of the group react in each situation? When there is agreement between the first and second person, is the rest of the group more likely to continue the pattern of ordering beer? How about in the second situation when the second person orders differently from the first by ordering a mixed drink? Does that action made it socially normative for the remainder of the group to order drinks other than beer?

Sequential behavior plays an important role in determining group norms and individual behavior. Self-presentation and satisfying one's own goals are competing when individuals make choices (Ariely and Levav 2000). Asch's classic line experiment demonstrates the strength of complying to sequential group norms; many participants complied with group norms by giving an obviously incorrect answer in order to agree with the other group members (Asch 1955; Deutsch and Gerard 1955). Further, Asch's line experiment demonstrated that when there was only one confederate stating an incorrect answer, the participants gave a correct answer in almost every trial. When a second confederate was added, the pressure to conform increased, such that participants gave incorrect answers to conform almost 14% of the time (Asch 1955). While Ariely and Levav (2000) describe several group-level goals such as information-gathering, self-presentation, and minimizing regret, they do not address the formation of group norms to satisfy the self-presentation goals. Specifically, they speculate that an individual's goal of self-presentation in the presence of the group can either lead to uniformity or variety-seeking (Ariely and Levav 2000), but do not indicate under which conditions the group goal will be uniformity versus variety. That is the focus of our research – the formation of group level norms. Recall the earlier example of choosing a drink at happy hour; this is an example of sequential behavior; the first person voices his or her decision, and then the second person (the first follower) agrees with that decision by following suit. Our prediction is due to the first follower's agreement with the initial suggestion, making it normative for others to also conform by ordering beer. Sequential behavior prompts individuals to determine group norms and then balance self and group level goals when determining their own behavior.

Surprisingly, to our knowledge, no research heretofore has examined the process underlying the formation of group norms in a sequential behavior setting. Some research (Markus and Kitayama 1991; Yoon et al. 2011) has demonstrated that the goal of seeking variety versus uniformity depends on the culture (i.e., collectivist or individualistic). We examine the role of the second decision maker, hereafter referred to as the first follower, on the determination of group norms. We propose that the group norm will be influenced more strongly by the behavior of the first follower, rather than the leader of the group. Our central thesis is that the leader has the power to make the first decision, but it is not until that behavior is emulated by the first follower that a norm is enacted.

Our research shows that the behavior of the first follower, versus the leader, most strongly influences this group norm in sequential behavior. We argue that the main effect of the first follower is significant, but importantly it is the comparison of the first follower's behavior to that of the leader that shapes group norms. We argue that the more similarly the first follower behaves to the leader, the more uniformity the group will seek. In contrast, the more the first follower deviates from the leader's behavior, it will become more acceptable for the group members to express different opinions and take contrasting actions.

Our theoretical contributions are four-fold. First, this research advances the literature on social influence in which there is a sequential process of expressing behaviors. To our knowledge, this is the first paper to examine the process underlying the formation of group norms in a sequential behavior setting. Second, we not only qualify the findings of Ariely and Levav (2000), we further demonstrate its application in online behavior. This research also provides new substantive insights in the context of online behavior. Through the use of online review data, we demonstrate an explanation for subsequent reviewers' behavior based on the first follower. By replicating our findings in both an online and a face-to-face context, we are able to illustrate the robustness of the first follower effect on group norms. Third, we demonstrate the pivotal role of the follower in establish group norms in a sequential process. We bridge the gap between the followership literature and the marketing literature by assessing the impact of followers outside of managerial processes. Fourth, our proposed first follower effect opens up a new path of research for examining moderators and boundary conditions of the first follower's influence in group norm formation.

We show this effect across three studies. We present a field study (Study 1) where we demonstrate support for the first follower effect, and we demonstrate it through individuals seeking variety or uniformity when ordering at a restaurant. This field study supports our thesis in an organic setting at a local restaurant by showing that the group norm and subsequent behavior will either be to seek uniformity or seek variety contingent upon the behavior of the first follower. The next study (Study 2) uses a large secondary data set of Yelp reviews and demonstrates the impact of the first follower on group norms of review valence, but importantly we generalize the effect into a different context. An experiment (Study 3) demonstrates the effect in an experimental setting and explicates the process underlying the phenomenon. Specifically, we show that perceptions of a group norm mediate the effect of the first follower on within-group variation. Finally, we end with a discussion and directions for future research.

## 3.1 Theory and Hypothesis Development

### 3.1.1 Self-Presentation and Group Norms

People often make decisions to improve self-presentation even when this requires ignoring their own preferences. Ratner and Kahn (2002) show that self-presentation drives individuals to seek more variety in a public setting than they would if they were in a private setting, while Ratner et al. (1999) report that individuals take into account how others around them may perceive their actions, such that people will forego an option that is the preferred choice for the purposes of seeking variety in a public setting. Bearden and Etzel (1982) examine how purchase decisions for individuals were influenced by the presence of a reference group. They find different product features to be more important depending on the consumption situation (i.e., public vs. private), such that features related to image become more important in public consumption. Prior research shows that individuals will give up satisfying their own tastes for the sake of being perceived more favorably by the group (Deutsch and Gerard 1955; Asch 1956; Schlenker, Britt and Pennington 1996).

The literature on normative influence indicates that individuals want to conform to beliefs and preferences of others; when exposed to the preferences of others, individuals seek to conform to the perceived group norm (Kaplan and Miller 1987). Specifically, Kaplan and Miller (1987) argue that normative influence will impact judgmental matters such as writing a review or ordering at a restaurant, while informational influence will dominate for intellective issues such as finding the correct answer. In public settings where the individual is identifiable, people are more driven to conform to group norms (Singer, Brush and Lublin 1965; Zimbardo and Ebbesen 1970; Diener 1979). Individuals seek to conform to local norms of the group versus with an individual (Abrams and Hogg 1990; Hogg et al. 2004), and leaders that are considered to be more prototypical of the group norm are viewed as more effective (Hogg et al. 2006). Taken together, these findings seem to suggest that the group norm acts independently of the leader. Allen and Levine (1969) sought to qualify the Asch's (1955) classic line experiment by including a confederate to either offer social support by agreeing with the subject or extreme dissenting by giving an even more incorrect answer. They found that both types of confederates enabled the subject to give the correct answer (Allen and Levine 1969). They proposed that disagreement with the group by each type of confederate was able to discredit the group's accuracy. Their research lends evidence into the idea of the first follower effect, because it could be the act of each type of confederate offering an opinion different from the group that then changes the group norm. Through the act of a differentiated opinion, the subject will then choose to give a response different from the first person.

Research on between-group influence largely focuses on groups instructed to arrive at a consensus. To this end, opinions typically converge in group settings (Festinger 1950; Levine, Moreland and Ryan 1998). For example, Kaplan (1987) looks at how juries reconcile many different opinions to come to a consensus. Festinger (1950) examines social pressures arising from shared housing, and reports that a goal of uniformity compels individuals to communicate with one another about specific issues. Hinsz et al. (1988) finds that when interacting in small groups, people are more inclined to come to a consensus. In terms of uniformity versus variety-seeking behavior, Hsee et al. (1999) report that when differences between products are hard to distinguish, participants seek less variety. Yoon et al. (2011) argue that there is a cultural component to seeking uniformity versus variety, such that “collectivist cultures” versus “individualistic cultures” have a higher tendency to seek uniformity in sequential choice settings. In this case, the type of culture is a factor in seeking uniformity in a group. Next, we discuss research proposing the opposite effect, that individuals will strive for variety in groups.

While there is research showing that in groups, people will converge to the same opinion, there is contradictory evidence that people will seek more variety and differentiation of opinions. For example, contrary to the converging opinion argument, Ariely and Levav (2000) find that individuals differentiated their opinions by seeking more variety in within-group settings. Personality traits also lead to increased variety in group settings. Ratner and Kahn (2002) report that high versus low self-monitors choose more variety to make themselves appear more interesting. Individuals with a higher need for uniqueness are more likely to select products that other group members have not chosen (Snyder 1992). Uniqueness theory suggests that individuals have a desire to maintain “specialness” and differentiate themselves from others around them (Fromkin and Snyder 1980). Outside factors can also increase this need for uniqueness, such as product scarcity (Snyder and Fromkin 2012).

Under what conditions will the group norm be to seek a unified opinion versus a diversified opinion? Based on the work by Ariely and Levav (2000), one might conclude that the group norm will always be to seek variety. However, there is contradicting research arguing that groups come to a consensus and express a unified opinion (Hinsz et al. 1988). We propose that there is a moderating effect that determines the group norm. Research has not heretofore addressed the question of how a group norm forms in a sequential behavior setting. After the leader, or first decision-maker, has stated their preferences and made a choice, the norm could go any direction. However, our thesis is that once a second opinion is added to the first, the norm becomes concrete and identifiable.

### 3.1.2 Leadership and Followership

Prior research in social influence has demonstrated that the leader exerts a normative influence on establishing group norms (Hogg and Reid 2006). Kelley (1988) argues that groups are more effective when there is a single leader versus many leaders. Turning to the leadership literature, followers have been viewed as active participants in the leadership process (Meindl 1995; Chemers 2001; Van Knippenberg and Hogg 2003). With that group dynamic in mind, the role of the follower becomes pivotal in enabling effective leadership and cohesive groups.

The leadership and followership literature has addressed the role of the relationship between the leader and the follower in influencing the overall effectiveness of the leader. For example, Leader-Member Exchange (LMX) Theory posits that the relationship between the leader and follower as a supporting member of the dyad can increase leadership effectiveness (Graen and Uhl-Bien 1995; Uhl-Bien et al. 2014). The idea is that leaders and followers are “co-creators” of leadership outcomes (Fairhurst, Rogers and Sarr 1987; Fairhurst and Grant 2010).

Followers are key players in both supporting and empowering leader emergence. The follower-centric viewpoint states that without followers, there can be no leaders (Fairhurst and Uhl-Bien 2012; Uhl-Bien et al. 2014). The followership literature has addressed the role of the follower in enabling a leader to have power and influence by acting as an effective subordinate in the group (Carsten and Uhl-Bien 2013; Uhl-Bien et al. 2014) by taking on the follower identity and allowing another member to take the leader identity (DeRue and Ashford 2010) and conceding to a leader (Uhl-Bien and Pillai 2007). Kelley (1988) contends that an effective follower is able to both think critically and be an active participant in the organization. Followers have been studied as an active participant in increasing leader efficacy, goal accomplishment, trust, and spread of social influence (Gooty et al. 2010; Uhl-Bien et al. 2014).

While the leadership literature has addressed the role of the follower, the group norm literature has yet to consider the potentially pivotal role a follower can play in group norms. Shamir (2007) studied the role of leaders as moderators of followership outcomes, opposite to the traditional viewpoint. By flipping the causality of leaders and followers, researchers have been able to explore the role of followers more explicitly. For example, leadership identity creation is contingent upon how followers in the group interpret those identities (Lord, Brown and Freiberg 1999), and characteristics of both leaders and followers have been shown to determine leadership outcomes (Lord et al. 2001).

### 3.1.3 Sequential Choice and the First Follower

Ariely and Levav (2000) investigate sequential choice in group settings and explore the phenomenon of having higher levels of variety in group versus individual ordering. They examine four types of goals when ordering in a group setting: satisfying one's own tastes, minimizing regret and avoiding losses, information gathering, and self-presentation. When participating in groups, individuals seek to balance two sets of goals: individual level goals and group level goals (Mackie and Goethals 1987; Ariely and Levav 2000). Satisfying one's own taste is an individual level goal, while self-presentation, information gathering, and minimizing regret are individual-group goals. They find that for self-presentation, individuals tend to order with more variety than they would if they did not take the decisions of other members of the group into account. While Ariely and Levav (2000) recognize that self-presentation is dependent on the group norm, they do not address how that norm is determined to order with more variety or more uniformity.

Our focal research question is explicating the process behind how group norms are formed. Ariely and Levav (2000) seem to suggest that all members of the group contribute equally to the overall group decision strategy, however, we demonstrate that it is the first follower, or the second decision maker, who is the key influencer. Importantly, we not only qualify their findings, we further demonstrate its application in online behavior. With opposing streams of research suggesting that groups seek convergence in opinion or variety of opinion based on personal traits such as a need for uniqueness (Snyder 1992), product scarcity (Snyder and Fromkin 2012), cultural differences (Yoon et al. 2011), and self-presentation (Ariely and Levav 2000), our research seeks to answer the question of how and why these group norms are determined. That is, whether the norm should be uniformity or variety, agreement or disagreement. We propose that the behavior of the first follower, relative to the leader, will govern the group norm.

In sum, we propose that the group norm is driven by the behavior of the second decision maker relative to the first. Specifically, we hypothesize that if the first follower makes the same choice or expresses a similar opinion to the leader, the rest of the group will tend to conform to this behavior. However, if the first follower behaves differently from the leader, then this will set the tone for other group members to diversify their behaviors. When the first follower makes a different choice or expresses a different opinion from the leader, this signals to the rest of the group that it is normatively acceptable to not conform.

## 3.2 Study 1: Brunch Field Study

The purpose of this field study was to assess whether the same group norm determination patterns observed in Studies 1 and 2 would obtain in a variety-seeking context among groups of people that know each other and are in person. To explore this research question, we conducted a field study using brunch orders at a local restaurant. We predicted that (a) when the first follower orders differently from the leader, the rest of the group will seek variety by ordering more different menu items from the leader, (b) when the first follower orders similarly to the leader, the remainder of the group will seek greater uniformity by ordering similar menu items to the leader, and (c) this effect will hold when controlling for table size.

### 3.2.1 Methodology

A local restaurant offers brunch on weekends, where diners sit down and order from a waitperson. Receipts were collected from brunch on Saturdays and Sundays from June 2016 to August 2016. The order in which each person at a table ordered was recorded by seat number, as well as the food items each person ordered. Because we are interested in sequential group choice in this study, in particular the role of the first follower's behavior relative to the leader, we needed to have at least 3 people at each table. Furthermore, to guarantee that all people at the table were able to hear each person's order, we restricted the maximum number of individuals at table to be six. In addition to this restriction, any table that included an order from the children's menu was excluded because it would be unclear whether the parent ordered for the child and the additional children's menu items would systematically alter the table variety in orders. This left us with 170 tables and 616 patrons. Table 12 shows summary statistics for the database of receipts.

**Table 12: Descriptive Statistics for Receipt Data (Study 1)**

| Variable | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Number of People at Table | 3.61 | .85 | 3 | 6 |
| Absolute Distance between Leader and First Follower | 1.14 | .34 | 0 | 6 |
| Measure of Average Group Difference at Table | 2.54 | .85 | 0 | 3.92 |

Once the receipt data had been collected, we measured the distance between each pair of menu items. To do this, we collected data from MTurk, where participants were asked to rate pairs of menu items on a Likert scale from 1 (very similar) to 7 (very different). The ratings of the participants were averaged for each pair of items, with six individuals rating each item pair. There were 28 different menu items, so the data was then put into a 28x28 matrix. The distance between identical items was coded as a 0, indicating no difference.

The first goal of the analysis was to visually and empirically verify that the MTurk participants' ratings exhibited face validity. We employed the use of multidimensional scaling to assess the pairwise distance between all of the menu items. Two dimensions were sufficient in this case, so we restricted dimensionality to two dimensions. The variance explained by the first and second dimensions was 28.6% and 19.3%, respectively. Figure 5 shows the results of the two-dimension multidimensional scaling. As can be seen in Figure 5, pizzas are generally clustered together in the top left corner, burgers and sandwiches are in the middle, while breakfast foods are along the right side. In addition, a cluster of healthier options emerged along the bottom left of the figure, including the salads and salmon. This lends support to the accuracy of the food pair ratings done by the participants.

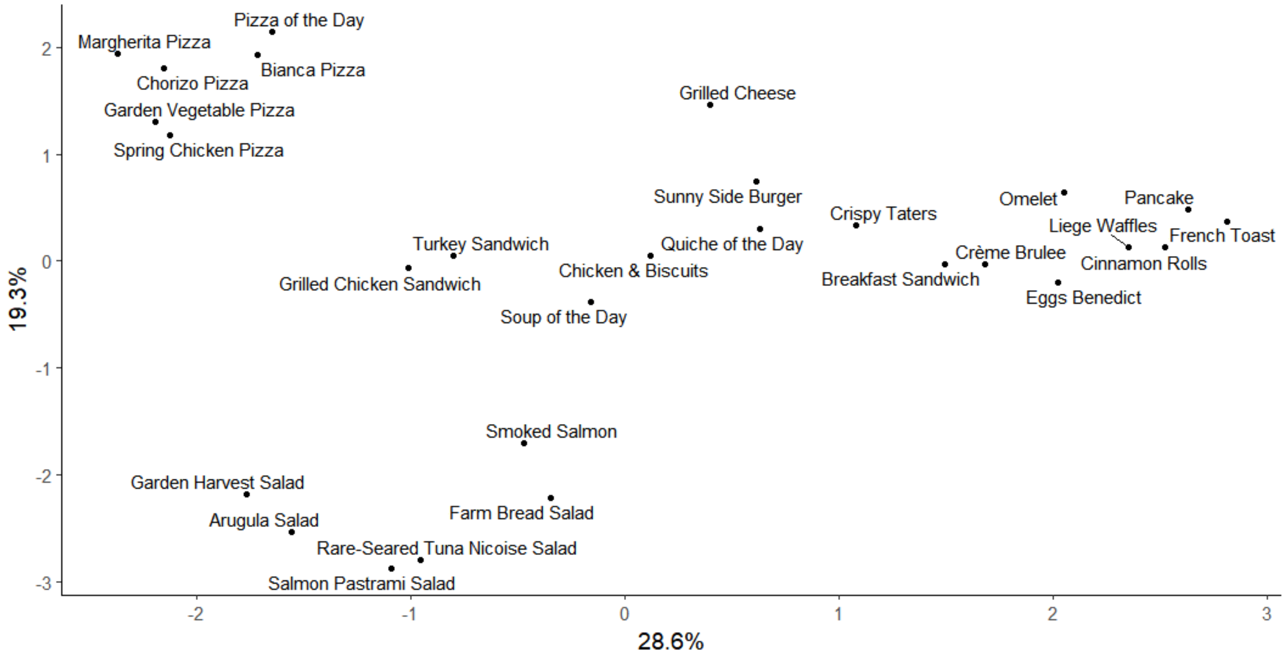



***Figure 5: Multidimensional Scaling of Distance Ratings (Study 1)***

The next step in analyzing this data was to compute distance scores for each table in the receipt data. We calculated the pairwise difference rating for each pair of menu items, and then used the average linkage method to measure overall group distance. The average linkage measure was used because it is less susceptible to noise and outliers as compared to other linkage methods. To calculate the group distance using the average linkage, each person's order was compared to every other person's orders at the table excluding the first follower, and the average value was taken.

$$Average\ Linkage = \sum\nolimits_{i,j=1,i,j\neq 2}^{n} \frac{dist_{ij}}{n}.$$

We excluded the first follower distance from each pair in the group distance calculation because the pairwise difference between the first follower and the leader is used as our independent variable to predict overall group distance and removing the first follower from the group distance calculation prevents artificial inflation of the proposed effect.

To illustrate how the group distance was calculated, consider a four-person table where the leader (A), third (B), and fourth person (C) ordered 3 different items, the similarity score differences between A's item (Spring Chicken Pizza) and B's item (Grilled Chicken Sandwich) is 2, between B's item (Grilled Chicken Sandwich) and C's item (Liege Waffles) is 5, and between A's item (Spring Chicken Pizza) and C's item (Liege Waffles) is 7, would be summed and divided by three, yielding an average group distance of 4.67. The difference between the leader and first follower's orders is simply the pairwise distance score between the two items, such that the more different the two items, the higher the distance score.

We estimated a model predicting the average group distance for each table (excluding the first follower) using the distance between the first follower and leaders' orders and the number of people at the table as predictors. We predict that when the first follower orders differently from the leader, the group will seek more variety than when the first follower orders similarly to the leader. Unfortunately, because we did not receive any demographic data from the restaurant, we were unable to include gender and age in the model. However, Study 3 controlled for age and gender, showing that neither was a significant predictor of review variance. This lends empirical support that controlling for age and gender in this field study would not alter the results.

### 3.2.2 Results

The model R-squared value was .345, and the overall model was significant ($F(2,167) = 44.02$, $p < .001$). The results of the regression analysis are presented in Table 13. As we predicted, the distance between the first follower and leader was significant ($b = .238$, $p < .001$), revealing that as the first follower diverges more from the leader, the average table variety increases. The table size was also significantly related to the average group distance (b = .182, *p* < .01), indicating that the more people at a table, the higher the variety in orders[3].

**Table 13: Regression Results (Study 1)**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Intercept | .9453* | .2377 |
| First Follower Distance | .2382* | .0280 |
| Table Size | .1823* | .0612 |
| Model Fit Statistics | F (2, 167) = 44.02<br>p-value < .001<br>$R^2$ = .3452 | |

*indicates significance at .01 level

### 3.2.3 Robustness Checks

For robustness, we also computed the a priori probabilities of the food orders placed at each table and used that as a control variable. The first step was to use the leader's (i.e. the first person at each table) order to calculate an a priori probability of a menu item being ordered. Table 10 below shows the probabilities of each menu item being ordered. For three of the menu items, there were no leaders that ordered them, so the probability was placed as $\varepsilon > 0$ to prevent a zeroing out of the table probabilities. For the a priori probabilities of menu items, see Table 14.

[3] An additional model specification was run including an interaction term for first follower distance and table size, but this was not significant, and results remained consistent.

**Table 14: Probability of Each Menu Item (Study 1)**

| Menu Item | Probability |
|---|---|
| Arugula Salad | 1.2% |
| Bianca Pizza | 1.2% |
| Biscuits and Gravy | 0.0% |
| Breakfast Sandwich | 7.0% |
| Grilled Chicken Sandwich | 5.7% |
| Chorizo Pizza | 0.8% |
| Chicken & Biscuits | 11.1% |
| Cinnamon Rolls | 0.8% |
| Crème Brule | 0.4% |
| Garden Vegetable Pizza | 1.6% |
| Eggplant | 0.0% |
| Eggs Benedict | 4.9% |
| Farm Bread Salad | 1.6% |
| French Toast | 0.0% |
| Grilled Cheese | 1.2% |
| Garden Harvest Salad | 4.9% |
| Margherita Pizza | 6.6% |
| Omelet | 8.2% |
| Pancake | 1.2% |
| Quiche of the Day | 13.5% |
| Salmon Pastrami Salad | 1.2% |
| Smoked Salmon | 4.9% |
| Soup of the Day | 0.8% |
| Pizza of the Day | 2.0% |
| Spring Chicken Pizza | 2.9% |
| Sunny Side Burger | 7.0% |
| Crispy Taters | 0.4% |
| Thai Chicken | 0.4% |
| Rare-Seared Tuna Niçoise Salad | 3.3% |
| Turkey Sandwich | 0.8% |
| Farmstand Vegetable Burger | 0.4% |
| Liege Waffles | 3.7% |

For each table, the probability of that combination was calculated by multiplying the probability of each dish being ordered together:

$$p(table) = \prod_{i=1}^{n} p(itemi),$$

where the probability of item i is the a priori probability of item i being ordered and n is the total number of patrons at a table. We then use the table probability as a control variable and find consistent results (see Table 15).

**Table 15: Regression Results with Table Probability (Study 1)**

| Variable | Coefficient | Standard Error |
|---|---|---|
| Intercept | 1.3618* | .2614 |
| First Follower Distance | .2369* | .0271 |
| Table Size | .0980* | .0644 |
| Table Probability | -665.12* | 196.68 |
| Model Fit Statistics | $F(3, 166) = 34.99$<br>p-value < .001<br>$R^2 = .3874$ | |

*indicates significance at .01 level

### 3.2.4 Discussion

Study 1 reveals that the group norm is influenced by the behavior of the first follower relative to the leader. These results indicate that when the first follower orders similarly to the leader, the group norm becomes uniformity. When the group norm is to seek uniformity, the rest of the group is more likely to order similarly. However, when the first follower orders differently from the leader, this causes the group norm to be variety-seeking. When the group norm is to seek variety, there will be more diversity in the table's ordering patterns. Taken together, these results indicate that the first follower's actions relative to the leader determine whether the group norm will be to seek variety or uniformity.

The first goal was to verify the use of pairwise difference ratings, which validated our measure of group distance. The multidimensional scaling of pairwise differences both heuristically and empirically validates this. In addition, the results of the multidimensional scaling demonstrate that people are able to judge the similarity of menu items in a restaurant setting. Finally, we demonstrate the first follower effect in a completely different context from the first two studies. The results of this field study further lend additional support to our core hypothesis.

Methodologically, we contribute a more finely grained method for measuring group diversity when the choice variables are categorical. While Ariely and Levav (2000) use a variety index measure which was simply the number of different dishes ordered divided by the total number of people at the table, we used a much more nuanced approach. The variety index does not take into account the varying levels of similarity between dishes or potential dietary restrictions from precluding an identical order. Take for example a scenario of a two-person table in which (a) person 1 orders a chicken salad and person 2 orders a steak salad, and (b) person 1 orders a chicken salad and person two orders a burger. Both scenarios would yield a variety index of .5, however a chicken salad and a steak salad are much more similar to one another than either is to a burger. Using our pairwise similarity approach to operationalize average group distance provides a more sensitive and accurate method for measuring group diversity.

Importantly, this field study once again demonstrates the first follower phenomenon with a consequential measure, actual ordering behavior. This further shows that this effect holds offline among groups that are already acquainted in a face-to-face situation, lending further support to our core hypothesis. Our field study implies that groups with well-established relationships are once again susceptible to the first follower effect. In addition, Study 1 demonstrates that when the first follower orders similarly to the leader, they signal to the remainder of the group that it is normative to be order uniformly.

### 3.3 Study 2: Secondary Data Set of Yelp Data

The purpose of this study is to (a) formally demonstrate the existence of the first follower phenomenon we have proposed, and (b) show initial evidence in an online context that first follower behavior moderates subsequent group behavior. To test our thesis, we used Yelp.com, a website that publishes reviews on local businesses written by customers. This study used a large secondary data set of Yelp reviews, which is available to download as part of the Yelp Dataset Challenge (Yelp 2017). Yelp reviews are an excellent context to test the first follower normative influence in online reviews, for several reasons. First, because each review is time-stamped, we can cleanly determine the leader and first follower in each business's reviews. Second, reviewers are able to see prior reviews before they contribute their own review, such that they have the ability to be influenced by prior reviewer behavior. Finally, reviews on Yelp are public, and therefore are a consequential measure of group norm conformity.

#### 3.3.1 Data

As of June 2017, the Yelp review dataset had 144,000 businesses and over 4 million reviews (Yelp 2017). Because of the enormity of the data, we focused our analysis to businesses located within the state of Pennsylvania. This left us with a large sample of 8,091 businesses and 179,774 reviews. Businesses ranged from restaurants to salons and car dealerships to clothing retailers. The wide variety of businesses adds robustness to this study, as we are not simply restricting the analysis to a certain type of business. Importantly, the dataset contains every review posted for each business. Each review entry contained the business name, date and time of posting, the review text, the city, zip code, state, and the star rating of the business.

### 3.3.2 Measures

### 3.3.3 Sentiment score

We measured the sentiment of each Yelp review in the dataset. To do this, we employed the VADER sentiment analyzer to measure the review valence. VADER (Valence Aware Dictionary for sEntiment Reasoning) has been validated extensively and performs almost as well as human coders (Gilbert and Hutto 2014). Furthermore, when comparing VADER with LIWC (Linguistic Inquiry Word Count), a more commonly used approach in marketing research, Gilbert and Hutto (2014) report that Vader outperforms LIWC's sentiment analysis in both social media and other domains. In addition, LIWC is unable to interpret intensity, acronyms, emoticons, or slang, all of which appear frequently in social media posts (Davidov, Tsur and Rappoport 2010).

To illustrate the performance of LIWC versus VADER with sentiment analysis, consider the following two sentences: (1) "This restaurant is okay," and (2) "This restaurant is amazing." The second sentence clearly shows more positive emotion, but LIWC rates the positive emotions for the first and second statements identically (Pennebaker, Booth and Francis 2007). By contrast, VADER sentiment analysis rates the first statement as .296, and the second statement a .586, capturing the greater positivity of the second statement. In the context of Yelp reviews, it is pivotal that sentiment analysis is able to accurately capture the difference in valence between those two statements. Compared to LIWC, VADER is more accurate, better equipped to analyze social media text, and is freely available.

VADER uses a dictionary of positive and negative words to classify text. The base dictionary used in VADER was founded in previously established sentiment dictionaries, such as LIWC, Affective Norms for English Words (ANEW), and General Inquirer (GI). These dictionaries were supplemented using human coders to include measures of sentiment intensity, including punctuation (i.e. '!' versus '!!!'), capitalization, emoticons, modifiers (i.e. 'very'), negations (i.e., 'but'), and tri-grams, which involves using the three words prior to a sentiment word (Gilbert and Hutto 2014). VADER calculates a multi-dimensional measure that is the proportion of language that falls into each of the three categories: positive, negative, and neutral, respectively, as well as a unidimensional measure, discussed below.

We primarily used VADER's standardized measure of sentiment called the compound score, which is a continuous value between -1 and +1 (Gilbert and Hutto 2014). A score close to -1 indicates that the review is very negative, while a score close to +1 indicates a review that is very positive. We use this unidimensional sentiment measure, hence forth referred to as "standardized sentiment", because it is the most informative single-dimension metric (Gilbert and Hutto 2014). In addition, we used two multidimensional positive and negative sentiment scores, which indicate the proportion of text that falls into the positive category and negative category, respectively.

Because review text can have some ambiguity associated with it, we also use the positive and negative multidimensional sentiment scores. Further, we rely on the positive and negative sentiment scores of the review text versus the star ratings because of the ambiguity associated with star ratings. For instance, Mudambi and Schuff (2010) demonstrate that while a rating of three out of five stars could indicate indifference, it could also be a combination of positive and negative sentiment counteracting each other. We are able to disentangle this problem with the positive and negative sentiment scores, which provide a clearer analysis of the sentiment expressed in each review.

In order to validate the use of VADER's sentiment measures, we ran an ordinal logistic regression model predicting the star rating of each review using the positive and negative multidimensional sentiment scores calculated by VADER based on the review text. We then used the predicted and actual star ratings to calculate the mean absolute error (MAE) of the star ratings:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|,$$

where n is the total number of reviews, $\hat{y}_i$ is the predicted star rating and $y_i$ is the actual star rating. We find that the MAE is .81. While VADER's sentiment scores do not yield a perfect accuracy for star ratings, we feel that a MAE of .81 is sufficient, indicate that on average, we are within one star rating of the actual value. Next, we discuss the dependent variables used for this study.

### 3.3.4 Dependent variables

*Leader-Third person absolute difference.* This measure is the absolute difference between the sentiment scores of the leader (i.e., the first review) and the third person to review. This is designed to measure the spread of opinion between the leader and third person, excluding the first follower's behavior. This measure excludes the first follower behavior, as to not artificially inflate the results. The equation is presented below:

$$TPD = |x_1 - x_3|,$$

where $x_1$ is the unidimensional sentiment score of the first reviewer, and $x_3$ is the unidimensional sentiment score of the third reviewer. A larger difference score indicates that the third person deviated from the leader more in terms of review sentiment.

*Leader-Third Person Euclidean Distance.* This measure is the Euclidean distance of the two dimensional positive and negative sentiment scores of the leader (i.e., the first review) and the third person to review. This is designed to measure the spread of opinion between the leader and third person. The equation is presented below:

$$ED = \sqrt{\sum_{i=1}^{2}(q_i - p_i)^2},$$

where $q_1$ is the first person's positive sentiment score, $p_1$ is the third person's positive sentiment score, $q_2$ is the first person's negative sentiment score, $p_2$ is the third person's negative sentiment score, and ED represents the Euclidean distance between the sentiment of the first and third person.

### 3.3.5 Independent variables

Next, we describe the key variables of interest and how each was calculated. For the summary statistics of each variable, see Table 16.

*Leader's sentiment score.* This is the sentiment score of the first review posted for a business.

*First follower's sentiment score.* This is the sentiment score of the second review posted for a business.

*Sentiment difference.* This is the absolute difference in sentiment scores between the leader (i.e., the first reviewer) and the first follower (i.e., the second reviewer). A larger difference indicates that the first follower deviated more from the leader.

*Leader-First Follower Euclidean Distance.* This is the Euclidean distance between the positive and negative sentiment dimensions of the leader and first follower. A larger distance indicates that the first follower deviated more from the leader.

*Time Lag*. This is the time difference in days between with the first and second reviews were posted online. This is used to control for possible time effects.

*Stars*. This is the overall rating on a scale from 1 (bad) to 5 (great) for each business. Using the stars as a control variable is a more conservative way to analyze proposed relationships. We are interested in the impact of the sentiment of reviews of the leader and first follower and the difference impacting subsequent reviews. By including the stars as a control variable, we are accounting for any other reasons we may see variability within businesses. For robustness, we also ran the model without stars and still find that the difference between the leader and first follower's sentiment is a significant predictor of both the third person variance and within group variance.

**Table 16: Descriptive Statistics for Yelp Data (Study 2)**

| Variable | Variable Description | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| diff_3L | Absolute Difference of Third Person's Standardized Sentiment Score from Leader | .45 | .57 | 0 | 1.99 |
| ed_3L | Euclidean distance of Third Person's positive and negative sentiment from leader's | .13 | .09 | 0 | .67 |
| ed_FL | Euclidean distance of First Follower's positive and negative sentiment from leader's | .14 | .09 | 0 | .88 |
| grpvar | Group Sentiment Variance (excl. First Follower) | .30 | .32 | 0 | 1.93 |
| $comp_L$ | Leader's Sentiment Score | .66 | .53 | -1 | 1 |
| $comp_{FF}$ | First Follower's Sentiment Score | .63 | .56 | -1 | 1 |
| comp_diff | Absolute Difference between Leader and First Follower's Sentiment Scores | .43 | .56 | 0 | 1.97 |
| Time_lag | Time Difference in days between Leader and First Follower's Review | 332.08 | 400.78 | 0 | 3,081 |
| Stars | Business's Average Star Rating | 3.63 | .93 | 1 | 5 |

### 3.3.6 Method

We estimated two linear models. The first model was done by predicting the third person's absolute difference from the leader using the leader's compound sentiment score, the first follower's compound sentiment score, and the compound difference score, while controlling for the time lag and average business star rating. The linear regression models are presented below:

$$\begin{aligned}\mathrm{TPD} = \beta_0 + \beta_1(\mathrm{sentiment_L}) + \beta_2(\mathrm{sentiment_{FF}}) + \beta_3\ (\mathrm{sentiment_{diff}}) + \beta_4(\mathrm{time\ lag}) \\ + \beta_5(\mathrm{stars}) + \epsilon_\mathrm{i}\end{aligned}$$

where TPD is the third person difference from the leader, $\mathrm{sentiment_L}$ represents the sentiment of the first review (i.e. the leader), $\mathrm{sentiment_{FF}}$ is the sentiment of the second review (i.e. the first follower), $\mathrm{sentiment_{diff}}$ is the sentiment difference of the first and second review, the time lag is the time difference in days between the first and second reviews, and stars represents the average review for the business.

$$\begin{aligned}ED_{L,3} = \beta_0 + \beta_1(\mathrm{pos_L}) + \beta_2(\mathrm{pos_{FF}}) + \beta_3\ (neg_\mathrm{L}) + \beta_4\ (neg_\mathrm{FF}) + \beta_5\left(ED_\mathrm{L,FF}\right) + \beta_6(\mathrm{time\ lag}) \\ + \beta_7(\mathrm{stars}) + \epsilon_\mathrm{i},\end{aligned}$$

where $\mathrm{ED_{L,3}}$ is the Euclidean distance between the leader and the third reviewer, $\mathrm{pos_L}$ and $\mathrm{neg_L}$ are the positive and negative sentiment scores of the leader, $\mathrm{pos_{FF}}$ and $\mathrm{neg_{FF}}$ are the positive and negative sentiment scores of the first follower, $\mathrm{ED_{L,FF}}$ is the Euclidean distance between the leader and first follower, the time lag is the time difference in days between the first and second reviews, and stars represents the average review for the business.

### 3.3.7 Results

Modeling the third person difference yields an R-squared value of .260. Table 17 reports the results of the analyses. We find a negative main effect of the leader's sentiment score (b = -.358, $p < .001$) and a positive main effect of the first follower's sentiment score (b = .072, $p < .001$). Importantly, the sentiment valence difference between the leader and first follower is positive and significant (b = .144, $p < .001$), indicating that the more the first follower disagreed with the leader, the higher the difference between the third reviewer and the leader. In addition, the time lag between the first two reviews was significant (b = .000, $p = .004$), indicating that the time difference between the behavior of the first and second reviewer postings was relevant to the subsequent reviews. The average star rating for the respective business was negative and significant (b = -.118, $p < .001$), indicating that the higher the average rating of the business, the lower the variation in sentiment across the reviews.

**Table 17: Yelp Reviews Regression Results using Third Person Difference (Study 2)**

| Variable | Variable Description | Third Person Difference from Leader |
|---|---|---|
| Intercept | Intercept | .993** (.027) |
| $comp_L$ | Leader's Sentiment Score | -.358** (.012) |
| $comp_{FF}$ | First Follower's Sentiment Score | .072** (.013) |
| diff_comp | Sentiment Difference between Leader and First Follower | .144** (.014) |
| time_lag | Time Difference in days between Leader and First Follower's Review | .000* (.000) |
| Stars | Business's Average Star Rating | -.118** (.007) |
| Model Summary | | $R^2 = .260$ F(5, 8085) = 560.5 $p < .0001$ |

Modeling the Euclidean distance yields an R-squared value of .260. Table 18 reports the results of the analyses. We find positive main effects of the leader's positive sentiment score (b = .1741, $p < .001$) and negative sentiment score (b = .2764, $p < .001$). We find negative main effects of the first follower's positive sentiment score (b = -.0633, $p < .001$) and negative sentiment score (b = -.0978, $p < .001$). Importantly, the Euclidean distance between the leader and first follower is positive and significant (b = .2444, $p < .001$), indicating that the more the first follower differentiated from the leader's opinion in terms of both positive and negative sentiment, the higher the distance between the third reviewer and the leader.

**Table 18: Yelp Reviews Regression Results using Euclidean Distance (Study 2)**

| Variable | Variable Description | Third Person's Euclidean Distance from Leader |
|---|---|---|
| Intercept | Intercept | .077** (.005) |
| $POS_L$ | Positive Sentiment of Leader | .174** (.010) |

| | | |
|---|---|---|
| $NEG_L$ | Negative Sentiment of Leader | .276** (.020) |
| $POS_{FF}$ | Positive Sentiment of First Follower | -.063** (.010) |
| $NEG_{FF}$ | Negative Sentiment of First Follower | -.098** (.020) |
| $ED_{L,FF}$ | Euclidean Distance of Leader and First Follower | .244** (.012) |
| time_lag | Time Difference in days between Leader and First Follower's Review | .000 (.000) |
| Stars | Business's Average Star Rating | -.001** (.001) |
| Model Summary | | $R^2 = .121$ $F(7, 8083) = 159.1$ $p < .0001$ |

### 3.3.8 Discussion

We will now discuss the model results. A more positive leader review is associated with a decrease in sentiment variance for the remainder of the group. Importantly, as the absolute difference between the sentiment of the leader and first follower increases, the higher the sentiment variance for the remainder of the reviews. This indicates that while the leader acts as a reference point for subsequent reviews, it is not until the first follower reviews either similarly or differently to the leader that the norm is established. When the follower writes a review that is similar in sentiment to the leader, the remainder of the reviewers tend to subscribe to that norm when writing their own reviews. However, when the first follower writes a review that is dissimilar in sentiment to the leader, the remainder of the reviewers are normatively free to express varying opinions.

Through the use of a large secondary dataset, we find that the behavior of the third person in the sequential group can be predicted by using the behavior of the first follower relative to the leader. Our results also provide evidence that the behavior of the first follower relative to the leader influences the general variation in reviews for the business. This study is especially powerful because it demonstrates our core prediction in a relatively anonymous online setting, where no personal relationships between reviewers exist. In addition, by using group variance, we find that this effect persists in large group settings. Now that we have examined the general phenomenon, we turn to an experiment to demonstrate both causation and the underlying process.

## 3.4 Study 3: MTURK Yelp Experiment

The secondary dataset in Study 2 provides initial evidence of the first follower effect. In Study 3, we sought to demonstrate the process in terms of the moderating role of the first follower behavior and the mediating role of the perception of a group norm. We kept the same context, online reviews, and manipulated which reviews participants would see before writing their own review. We began by performing a pretest on the restaurant review stimuli.

### 3.4.1 Pretest of Restaurant Reviews

We ran a pretest of two positive and two negative restaurant reviews on Amazon’s Mechanical Turk (MTurk). The goals of this pretest were four-fold. First, we wanted to demonstrate that people can discern that there is a difference in sentiment of online restaurant reviews. Second, we needed to ensure that there was no significant difference within the two positive reviews and the two negative reviews. Third, we also needed to ensure that there was a significant difference in sentiment between the pairs of positive and negative reviews. Finally, we wanted to determine whether the Vader compound score was representative of the perceived difference in sentiment of the positive and negative stimuli.

For details of the exact stimuli used, see Appendix A. The stimuli were matched for valence using the Vader compound sentiment scores, such that the positive review compound scores were each -.899, and the negative review compound scores were .975. Each participant was presented with the four reviews, two of which were positive and two of which were negative (n=47, 47% Male). Participants rated the sentiment of each review on a Likert scale from 1 (extremely negative) to 7 (extremely positive). The results indicate that there was no significant difference between the two positive reviews ($M_{p1}$ = 6.32, $M_{p2}$ = 6.53, t= -1.49, $p$ = .142), nor the two negative reviews ($M_{n1}$ = 1.83, $M_{n2}$= 1.72, t = .93, $p$ = .359). There are significant differences between each of the four pairs of positive and negative reviews ($p < .0001$, respectively).

### 3.4.2 Method

Once we had pretested the stimuli, we used the same review text in our experiment. This study was conducted on MTurk and employed a 2 (Leader Sentiment: Positive, Negative) x 3 (First Follower Sentiment: Positive, Negative, Control) between subject design (N = 478, 48.2% Male, $M_{age}$ = 37.3). Participants were asked to select one of the following restaurants that they had been to within the past 90 days: Olive Garden, Chili's, Applebee's, or TGI Fridays. If they had not been to one of those, they were dismissed from the study, removing 135 potential participants. Participants were told that they would see reviews from the restaurant that they had selected.

In each condition, the participant read one or two of the pre-tested restaurant reviews and were told that they were both from the restaurant they had selected in the previous question. The first review has a "first to review" indication as is done on the Yelp website itself (see Appendix A). The first review shown was either positive or negative, depending on the condition. The second review either positive, negative, or not shown (i.e., the control condition). After reading the review(s), the participant was then asked to write his or her own review for the restaurant. Additionally, each participant was asked to indicate their level of agreement with the statement, “I feel that the reviews indicate that people share a common opinion about the restaurant” on a Likert scale from 1 (strongly disagree) to 7 (strongly agree).

The dependent variable was variation between the compound sentiment of the review each participant wrote and the compound sentiment score of the leader review. Gender neutral names of the reviewers and similar numbers of reviews, photos, and friends were used as to not add any noise to the experiment. The mediator was measured as the perceived group opinion, such that participants rated if they felt there was a common opinion about the restaurant on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). We hypothesized that when the first follower and leader reviews had matching sentiment, the perception of a common group opinion would be higher, and when the first follower and leader reviews had mismatching sentiment, the perception of the common group opinion would be lower.

To test for process, a moderated mediation analysis was performed using contrast coding (Hayes 2017). Figure 6 shows the proposed moderated mediation model. In order to formally test our proposed framework, we performed a moderated mediation analysis using Hayes’ PROCESS Model 7 with 10,000 bootstrap samples, with leader behavior as the predictor (positive = 1, negative = -1), first follower condition as the moderator (positive = 1, control = 0, negative = -1), belief of a common group opinion as the mediator, and review difference as the dependent variable (Hayes 2017). Table 19 reports all results for the moderated mediation models, without control variables (Model A) and with control variables for age, gender, and restaurant choice

(Model B). Table 19 reports the indirect effects of the moderator. Since the results for the two models are consistent (see Tables 19 and 20), we focus our discussion on Model A.

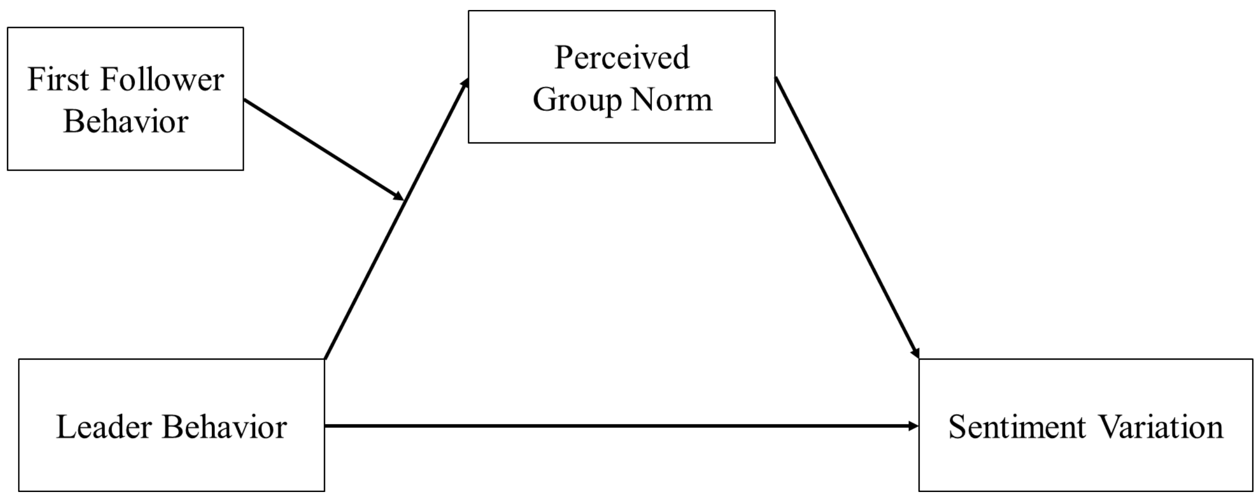



**Figure 6: Moderated Mediation Framework**

**Table 19: Results of Moderated Mediation (Study 3)**

| Model | Model A: Without Covariates | | | | Model B: With Covariates | | | |
|---|---|---|---|---|---|---|---|---|
| Antecedent | M (Common Opinion) | | Y (Difference from Leader) | | M (Common Opinion) | | Y (Difference from Leader) | |
| | Coeff. | SE | Coeff. | SE | Coeff. | SE | Coeff. | SE |
| Constant | 4.584*** | .069 | 1.047*** | .054 | 4.715*** | .329 | 1.073*** | .101 |
| X (Leader) | .315*** | .069 | -.616*** | .018 | .319*** | .069 | -.615*** | .018 |
| M (Common Opinion) | --- | --- | -.030** | .011 | --- | --- | -.031** | .011 |
| W (First Follower) | .180* | .084 | --- | --- | .171* | .084 | --- | --- |
| (X*W) Leader*First Follower | .763*** | .084 | -.023** | .009 | .771*** | .084 | -.024** | .009 |
| Age | | | | | -.008 | .006 | -.001 | .002 |
| Gender | | | | | -.111 | .140 | -.013 | .037 |
| Restaurant 1 | | | | | .165 | .263 | .016 | .069 |
| Restaurant 2 | | | | | .284 | .256 | .001 | .067 |
| Restaurant 3 | | | | | .194 | .278 | .047 | .073 |
| Model Summary | $R^2 = .188$ $F(3, 474) = 36.46$ $p < .0001$ | | $R^2 = .720$ $F(2, 475) = 609.63$ $p < .0001$ | | $R^2 = .193$ $F(8, 469) = 14.01$ $p < .0001$ | | $R^2 = .721$ $F(7, 470) = 173.05$ $p < .0001$ | |

**Table 20: Indirect Effects (Study 3)**

| Model | Model A: Without Covariates | | | | Model B: With Covariates | | | |
|---|---|---|---|---|---|---|---|---|
| Indirect Effects | M (Common Opinion) | | Y (Difference from Leader) | | M (Common Opinion) | | Y (Difference from Leader) | |
| | Coeff. | SE | Coeff. | SE | Coeff. | SE | Coeff. | SE |
| **Agreement** | 1.078*** | .108 | -.033** | .013 | 1.090*** | .109 | -.033** | .013 |
| **Disagreement** | -.448*** | .109 | .014** | .006 | -.453*** | .109 | .014** | .006 |
| **Control** | .315*** | .069 | -.010** | .004 | .319*** | .069 | -.010** | .004 |

*indicates significance at $\boldsymbol{p} < .05$ level
**indicates significance at $p < .01$ level
***indicates significant at $p < .001$ level

### 3.4.3 Results

We predicted that when the first follower is in agreement with the leader, the perception of a common group opinion will increase, and subsequently decrease the review difference from the leader, and when the first follower deviates from the leader, the perception of a common group opinion will decrease, and subsequently increase the review difference from the leader. The moderated mediation analysis indicated that leader behavior is moderated by first follower behavior, and that the perceived group norm, as operationalized by the belief of a common opinion, mediates the effect of leader behavior on review difference.

As predicted, the index of moderated mediation was significant (b = -.023, SE = .009, $CI_{95}$ [-.042, -.006]). These findings are consistent with our prediction that when the first follower diverges from the leader's behavior, the group norm will be that there is no common opinion, and the subsequent group members will behave varietally by writing a review that is less similar to the leader. Conversely, when the first follower conforms to the behavior of the leader, the group norm will be that there is a common opinion, and the subsequent members will continue to conform to that common opinion by writing a review that is more similar to the leader.

Next, we discuss the results of the conditional indirect analysis of first follower behavior relative to the leader on the perception of a common group opinion. A conditional indirect analysis showed that when the leader and first follower disagreed (i.e. one positive and one negative review), the effect was significant (b = -.448, SE = .109, $CI_{95}$ [-.662, -.234]), thereby indicating when there is disagreement, the participant views the group has having less of a common opinion. When the leader and first follower agreed (i.e. two positive or two negative reviews), the conditional effect was significant (b = 1.078, SE = .108, $CI_{95}$ [.866, 1.290]). Examining the control group, the effect is once again significant (b = .315, SE = .069, $CI_{95}$ [.180, .451])). These results indicated that when there was agreement between the leader and first follower, the opinion of the leader is moderated by the first follower, leading individuals to conform with the leader. However, when the first follower disagreed with the leader, the perception of a common group opinion is moderated by the behavior of the first follower, which subsequently leads individuals to diverge more from the leader. Finally, in the case where participants only see the leader's review, we find that participants view the norm as sharing a common opinion, though that effect is less pronounced versus in the agreement condition ($b_{agree}$ = 1.078, $b_{control}$ = .315).

Overall, results indicated that there was a significant interaction between leader review valence and first follower review valence on perceived group norms ($F(3, 474) = 36.46$, $p <$ .001). The main effect of the leader was significant in predicting the perception of a common opinion (b = .315, $p < .001$). Examining the first follower, we find a significant main effect (b = .180, $p = .032$). Importantly, the interaction between the leader and first follower is significant in predicting the perception of a common opinion (b = .763, $p < .001$), indicating that agreement between the leader and first follower leads to a perception of a common opinion. We also performed a simple slopes analysis to probe the effect of the leader and first follower interaction on common opinion using the variables in Model A. We found that there is a significant difference on common opinion when the first follower is in agreement versus disagreement with the leader ($M_{agree} = 5.159$, $M_{disagree} = 3.604$, $p < .001$); and the control condition versus disagreement ($M_{control} = 4.989$, $M_{disagree} = 3.604$, $p < .001$); but not for agreement versus the control condition ($M_{agree} = 5.159$, $M_{control} = 4.989$, $p = .302$). Table 21 shows the summary statistics by condition, and Figure 7 shows the interaction effects of first follower and leader behavior on the perception of a common group opinion.

**Table 21: Summary Statistics by Condition (Study 3)**

| **Leader and First Follower** | **Leader** | **First Follower** | **Common Opinion** | | **Difference from Leader** | |
|---|---|---|---|---|---|---|
| | | | **mean** | **variance** | **mean** | **variance** |
| Agreement | Negative | Negative | 4.72 | 2.30 | 1.47 | .21 |
| Disagreement | Negative | Positive | 3.53 | 3.31 | .28 | .12 |
| Control | Negative | --- | 4.58 | 2.10 | 1.56 | .15 |
| Agreement | Positive | Negative | 3.70 | 3.51 | 1.57 | .15 |
| Disagreement | Positive | Positive | 5.60 | .87 | .28 | .15 |
| Control | Positive | --- | 5.43 | 1.09 | .29 | .15 |

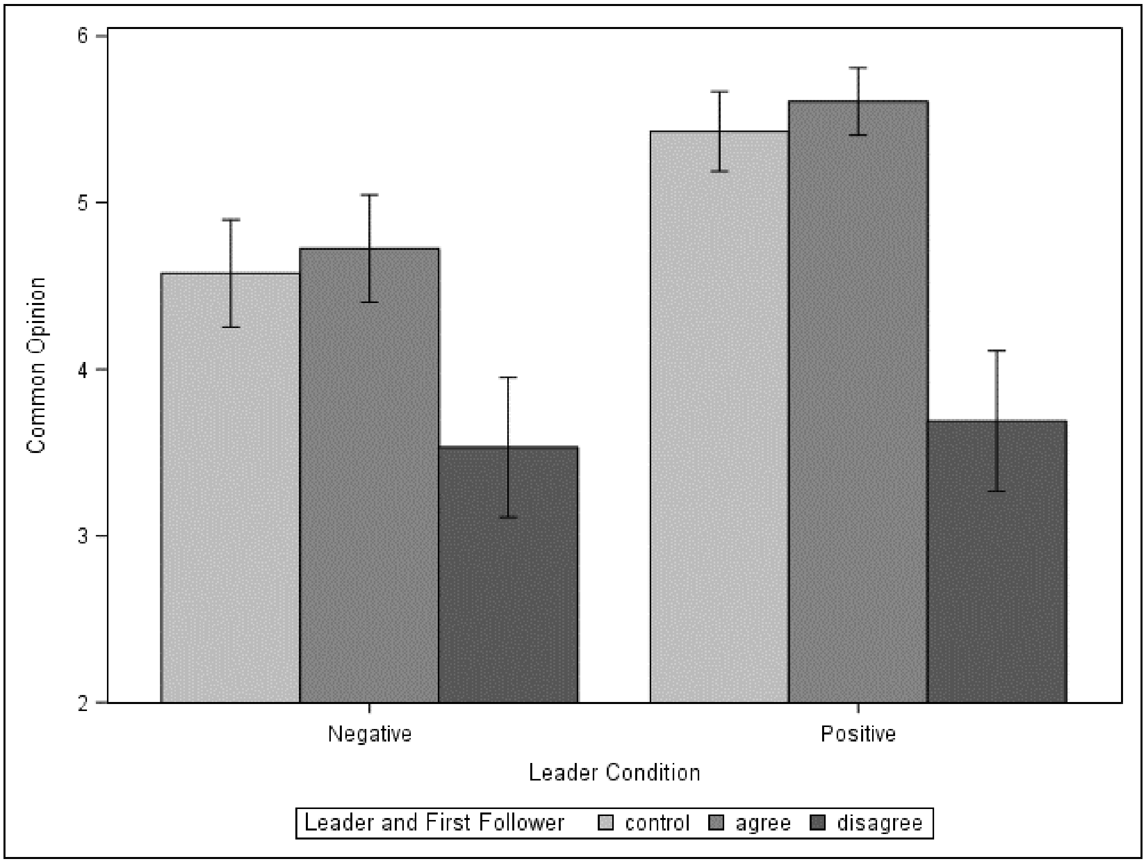



**Figure 7: Interaction of First Follower and Leader Behavior on Common Opinion (Study 3)**

Turning to the relationships of the variables of interest on review difference. The perception of a common group opinion was negatively related to review difference, as expected (b = -.030, $p < .01$). This indicates that an increase in perception that the group shares a common opinion will lead to a decrease in the reviewer's difference from the leader. In other words, the stronger the perception of a group norm, the more conformity we see to the leader. The results indicate that it is the behavior of the first follower *relative* to the leader behavior that predicts review difference from the leader. The leader had a direct effect on review difference (b = -.616, SE = .018, $CI_{95}$ [-.652, -.580]). Taken together with the moderated mediation, these results imply that while the leader has an impact on the review difference from the leader, the first follower's level of agreement versus disagreement from the leader plays a strong role in determining whether the participant contributes a review that is more (less) similar to the leader.

In terms of the indirect effects of the first follower condition on review difference, we find evidence of our central hypothesis. A conditional indirect analysis shows that when the leader and first follower disagreed (i.e., one positive and one negative review), the effect on review difference is significant ($b = .014$, $SE = .006$, $CI_{95}$ [.003, .027]). This indicates that when there is disagreement, the participant contributed a review with sentiment that differs more from the leader. When the leader and first follower agree (i.e., two positive or two negative reviews), the conditional effect is significant but negative ($b = -.033$, $SE = .013$, $CI_{95}$ [-.060, -.009]) – this indicates that agreement between the leader and first follower increases the similarity in review sentiment from the participant to the leader. For the control group where participants only viewed one review, the effect was once again significant ($b = -.010$, $SE = .004$, $CI_{95}$ [-.019, -.002]). Without a first follower review, participants differ less from the leader than they do in the disagreement condition ($b_{disagree} = .014$, $b_{control} = -.010$) and differ more from the leader than they do in the agreement condition ($b_{agree} = -.033$, $b_{control} = -.010$). These results lend further support for our central hypothesis.

### 3.4.4 Discussion

We find that first follower behavior moderates the effect between leader behavior on the perception of a common group opinion, which subsequently impacts the review difference from the leader of the third reviewer. When the first follower agrees with the leader, the perception of a common group opinion increases, and the review difference from the leader decreases. When the first follower disagrees with the leader, the perception of a common group opinion decreases, and the review difference from the leader increases. Our results seem to indicate that in the absence of a first follower, the group norm would be to agree with the leader's review. The interaction of the leader and the first follower, however, impacted the perception of a common opinion. These findings indicate that people are able to identify the group norm based on the behavior of the first follower relative to the leader, and they tend to follow the group norm of agreement (disagreement) by writing their own review which is similar to (different from) the leader.

This experiment shows the proposed effects in a controlled environment and illuminates the process. Through this experiment, we have demonstrated that the behavior of the first follower relative to the leader influences the perception of group norm, which then impacts subsequent behavior. Importantly, this experiment shows that when the first follower expresses a differing opinion from the leader, they signal to the remainder of the group that it is normative and okay to be different. The first two studies demonstrated the first follower effect in terms of online review valence, showing a real effect and the process behind the effect, respectively. Up until now, we have considered the context of online reviews and difference in terms of valence. The final study seeks to replicate the central proposition and show the same phenomenon in a different context – in person with variety-seeking behavior.

## 3.5 Discussion

This research makes a valuable contribution to the research on sequential behavior and social norms. Our findings provide evidence that the first follower plays a pivotal role in setting group norms. Specifically, it is the behavior of the first follower relative to the leader that determines the norms for the remainder of the group. Not only do group members choose a less preferred option to conform to these perceived group norms (Study 1), they also contribute their own written reviews with a more similar (varying) valence to the leader if the first follower conforms (diverges) from the leader (Studies 2 and 3). Our findings support the idea that the group leader can exert influence on the other group members, but we qualify this finding by providing evidence that the behavior of the first follower relative to the leader is plays a pivotal role in determining group norms in sequential choice settings.

Our findings imply that the first follower has the ability to determine whether the group norm should be agreement or disagreement. Described another way, the first follower can signal to the rest of the group that being different is acceptable and normative. As we demonstrated in Study 2 and Study 3, when the first follower disagrees with the leader, the remainder of the group is more inclined to express an opinion that differs from the leader. As we know from (Ariely and Levav 2000), when ordering at restaurants in groups, people seek more variety than they would if they were not in the presence of others. We qualify this finding and show that the first follower has the power to signal that it is okay to order similarly to the leader. Taken together, the first follower determines the group norms by either acting in agreement or disagreement with the leader.

The first follower phenomenon is a robust effect that holds in multiple contexts. The first follower effect is observed in restaurant field study (Study 1), and a large secondary dataset of Yelp reviews (Study 2), an experiment using restaurant reviews (Study 3). Moreover, we show that the behavior of the first follower relative to the leader impacts variety-seeking behavior in ordering at restaurants (Study 1) and online review valence (Studies 2-3). Importantly, we note that this phenomenon persists both in-person and online, implying that is a robust phenomenon.

### 3.5.1 Implications for Research

The implications for theory are threefold. First, Ariely and Levav (2012) seem to imply that all members of the group contribute equally to the overall group decision strategy. However, we have demonstrated that it is the first follower, or the second decision maker, who is the key influencer. Our results clearly establish the first follower's role in setting sequential group norms. Second, our research extends their findings to sequential online behavior. When people post anonymously, they are less concerned about self-presentation and social desirability (Joinson 1999), but we demonstrate that the first follower effect persists both in face-to-face and more anonymous online interactions. Third, while Ariely and Levav (2000) conclude that one should always order first to "maximize their consumption utility (pg. 289)" we show that the first follower has the power to sway the norm of the group in any direction, thus both maximizing their utility and being the taste-maker of the group.

### 3.5.2 Implications for Practice

This research has many implications for practice. Restaurants and waiters frequently face to task of upselling at restaurants (i.e., persuading patrons to spend more money during their dining experience). Common techniques of doing this include persuading customers to order drinks, appetizers, and desserts to increase the overall bill. Our research indicates that if a waitperson wants to increase the spending occurring at tables, they should encourage the wait staff to get two group members to demonstrate an interest in ordering an appetizer, drinks, or desserts. With the leader and first follower indicating the same preference, the group norm will be established, and the remainder of the table will be more inclined to order something as well.

Managerially, this research informs how review websites, such as Yelp.com and TripAdvisor.com, can increase authenticity in their crowd-sourced reviews. By implementing a review display sort that places two opposing viewpoints at the top of the reviews, the review website can encourage subsequent reviewers to express varying opinions. Two opposing reviews from a leader and first follower will create a group norm that encourages variety and differing opinions among reviewers. This will help to create a source of informative, honest, and reliable reviews.

This first follower phenomenon can be leveraged in many situations. Take for example a social network site, which will only foster diffusion if it is able to persuade a network of people to join. A targeted recruitment approach could seek out two people within the same social network to register. With a leader and first follower both indicating a norm of joining the social network site, the remainder of the social network will be more inclined to join as well.

## 3.6 Limitations and Future Research Directions

This work is subject to certain limitations. First, in the restaurant field study, we were not able to collect the gender, age, or nature of relationships of the tables. While the results replicate our prior findings, we were not able to control for those covariates in the restaurant field study. Secondly, because of computing power, we were not able to examine the entire Yelp data set, but instead focused on a subset of the review data. Future iterations of this research would include analysis of all businesses.

Future research could examine boundary conditions for the first follower effect. For example, future research could examine how sequential choice and first follower behavior is affected by the expertise of the first follower. By manipulating whether a commenter is “endorsed” as is done on websites like Amazon, individuals will be able to view the commenter as having more or less expertise. Future research directions could also measure expertise by examining text topic, tone, and language complexity. Language complexity of the first follower relative to the leader could potentially indicate expertise and authority, which would in turn exert more normative influence on the remaining group members. Villarroel Ordenes et al. (2017) utilized a more nuanced consumer sentiment, including sentence discourse and sentiment trends. Research questions could answer the conditions under which the sentiment trend in a review will be most influenced by the first follower.

In closing, our research has made a first step in further exploring sequential behavior by examining the influence of group members on group norms. We propose a moderating effect which explains the process behind a group norm that seeks agreement versus disagreement. This research makes a novel contribution by showing that it is the behavior of the first follower, or second decision maker, relative to the first that determines the group norm in sequential choice settings. Overall, this first follower effect has the potential to open many new streams of research questions, and we encourage researches to explore this phenomenon.

# APPENDIX A

## Robustness Checks: A Summary

1) **Were all the sponsored posts on both platforms, and should the data analysis be constrained to the posts that were on both?** All the sponsored posts appeared on the blog platform. In addition, of all the blog posts, only 7.6% were not cross-posted on Facebook. We included a robustness check running models in which we exclude the posts that were not cross-posted and found consistent results.

2) **Are results robust using LIWC to capture the content of the blog posts?** We ran an additional robustness check including a second way to measure post content sentiment, using positive and negative linguistic inquiry and word count (LIWC) emotions. We find no significant relationship between the positive or negative LIWC emotions on post engagement. This indicates that our measures of post content are sufficient to capture the variation in post engagement.

3) **Are results robust to other ways to measure the number of followers?** In the final models, we use the average number of Facebook and Twitter followers to operationalize the number of followers. We included Twitter in addition to Facebook because we were concerned that having only Facebook followers would be too context specific. We included other ways of operationalizing number of followers: (1) standardized unique monthly views (UMV) for blogger's webpage; (2) standardized number of Facebook followers, and (3) average of standardized number of Facebook followers and standardized UMV. Beginning with the blog post comment models, we find that the results are generally consistent, though UMV yields a nonsignificant effect on blog post comments (see Table WA11). Next, examining the Facebook post models, we again find consistent results for each measure of number of followers, with the exception of the functional content being significant in the model using only UMV (see Table WA12). For both the blog post comments model and the Facebook post likes models, we can see that the final model chosen has the lowest AIC and BIC of the tested specifications for number of followers (see Table 11 in main text).

4) **Are results robust to using alternative measures of post engagement for both blogs and Facebook?** We examine alternative measures for blog post and Facebook post engagement. First, for robustness we assess the valence of blog comments. In the current model, we assess the volume of blog comments and use that to model blog post engagement. We collected the text of each blog comment that was posted. We ran LIWC sentiment analysis on each comment. To calculate the total number of positive and negative comments, we used the "emotional tone" variable in LIWC. A higher number in emotional tone ranges from 0 to 100 and is "associated with a more positive, upbeat style;

a low number reveals greater anxiety, sadness, or hostility" (LIWC 2015). Therefore, we coded any score greater than or equal to 50 as a positive comment. Second, regarding alternative Facebook post engagement, we examine other dependent measures, including Facebook post comments and Facebook post shares. We find consistent results, whether we use the average of Facebook post likes and Facebook post comments or the average of Facebook post likes, comments, and shares.

5) **Are results robust to reverse-coding location in the blogger profile varimax rotation?** Noting that location had a negative effect on the blogger expertise factor, we reverse-coded location and reran the varimax rotation. We find identical results to our initial coding.

6) **Are the results robust to including the independent measures, number of blog post comments and number of Facebook post likes, in the Stage 1 Probit model?** We modeled an alternative specification in the Stage 1 model to include our independent variables. We find that the Stage 2 results are consistent with either Stage 1 specification.

7) **Are the results robust to separating the two blogger expertise variables?** We modeled an alternative measure of expertise by separating the blogger expertise into the two main variables that loaded onto the expertise factor (blogger credentials and blogger educational affiliation). We ran three new versions: (1) blogger credentials and blogger educational affiliation, (2) blogger credentials only, and (3) blogger educational affiliation only. We find that the results for the Facebook model are similar, as expected because expertise is not a significant driver in the model (see Table 11 in the main text). For the blog post model, the expertise × awareness intent interaction is driven primarily by the blogger credentials rather than educational affiliations.

8) **Are the results robust to scaling the number of blog post comments and the number of Facebook post likes by the number of followers?** For robustness, we ran two additional models, scaling each dependent variable by the number of followers and removing the number of followers variable from the right-hand side of the model. We find that while most results remain consistent in the blog post comments per follower model, hedonic content is not significant. In the Facebook post likes per follower model, we find that the results are unchanged, with the exception of hedonic content and giveaways.

9) **Are the results robust to a blogger fixed effects negative binomial regression?** We attempted to estimate a negative binomial fixed effects regression, using the blogger as the fixed effect. However, 198 of the observations were dropped from the blog post comments model and 216 observations were dropped from the Facebook post likes model because they only appeared once in the data set. We found that the majority of dropped observations occurred during campaigns with a trial intent, potentially biasing the results.

Bloggers who only appeared once were dropped, also potentially biasing the results. These dropped observations prevented us from estimating this model reliably.

10) **Is the model better represented through a Gaussian Copula with a Probit marginal selection model?** We ran Gaussian Copula models with a sample selection marginal component. The marginal model for selection showed similar results to the Stage 1 Probit model; similar blogger choice is a key predictor, as is the travel/foodie factor in blogger selection. Turning to the engagement marginal models, we again find consistent results to our Stage 2 models. For robustness, we modeled blog post comments and Facebook post likes using the natural log as well as a standardized version of the measures. The results remained consistent.

## Robustness Check Model Tables

### Model Results Excluding Posts Without Cross-Posting

| Variable | Blog Post Comments | Facebook Post Likes |
|---|---|---|
| Intercept | 1.9600** | 1.4636** |
| | (.1523) | (.1987) |
| Average number of followers (ln, mean-centered) | .3087** | .1962* |
| | (.0839) | (.0962) |
| Weekend post | -.1514 | .7215** |
| | (.1659) | (.2164) |
| Number of Facebook posts | N/A | .5354** |
| | N/A | (.0883) |
| Type of campaign – awareness | -.2189 | .7801** |
| | (.1449) | (.1891) |
| Blogger expertise (sum of credentials and education) | -.1104 | .0108 |
| | (.2008) | (.2571) |
| Functional value of post | -.0149 | .0442 |
| | (.0817) | (.0908) |
| Hedonic value of post | .2514** | .2240* |
| | (.0879) | (.1006) |
| Giveaway | .5049** | -.7831** |
| | (.1842) | (.2245) |
| Awareness × expertise | .7438* | -.4495 |
| | (.2937) | (.3368) |
| Awareness × functional | -.0858 | -.1510 |
| | (.1215) | (.1308) |
| Awareness × hedonic | -.1976 | -.4919** |
| | (.1313) | (.1353) |
| Awareness × giveaway | .4179 | .5112 |
| | (.3031) | (.3365) |
| Awareness × followers | -.0636 | .1459 |
| | (.1155) | (.1300) |
| Inverse Mills ratio | -.0002 | .1130 |
| | (.3488) | (.4222) |
| Overdispersion (α) | 3.9808** | 3.6915** |
| | (.1919) | (.1802) |
| AIC | 6378.98 | 5488.18 |
| BIC | 6455.10 | 5564.06 |
| –2 Log-likelihood $\chi^2$ | 100.67** | 217.20** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Model Results Including Positive and Negative LIWC Emotions**

| Variable | Blog post comments | Facebook post likes |
|---|---|---|
| Intercept | 2.0377** | 1.7715** |
| | (.2568) | (.4677) |
| Average number of followers (ln, Mean-Centered) | .3237** | .17242 |
| | (.0860) | (.1794) |
| Weekend post | -.1300 | .6560* |
| | (.1671) | (.2905) |
| Number of Facebook posts | N/A | .7423** |
| | N/A | (.1427) |
| Type of campaign – awareness | -.2424+ | .5697* |
| | (.1470) | (.2810) |
| Blogger expertise (sum of credentials and education) | -.3462 | -.4319 |
| | (.2527) | (.5179) |
| Functional value of post | -.0230 | -.0486 |
| | (.0825) | (.1437) |
| Hedonic value of post | .2623** | .5004** |
| | (.0883) | (.1670) |
| Giveaway | .4673* | -1.2493** |
| | (.1876) | (.3455) |
| Awareness × expertise interaction | .9106** | -.0335 |
| | (.3365) | (.6150) |
| Awareness × functional interaction | -.0523 | .1448 |
| | (.1255) | (.2103) |
| Awareness × hedonic interaction | -.2197+ | -.8077** |
| | (.1323) | (.2168) |
| Awareness × giveaway interaction | .4952 | .9343+ |
| | (.3087) | (.5228) |
| Awareness × followers interaction | -.0912 | .2427 |
| | (.1178) | (.2211) |
| LIWC Positive Emotion | .0098 | -.0025 |
| | (.0354) | (.0719) |
| LIWC Negative Emotion | -.1486 | -.1824 |
| | (.1130) | (.2394) |
| Inverse Mills ratio | -.0399 | .2602 |
| | (.3527) | (.6355) |
| Overdispersion (α) | 3.9945** | 2.9944** |
| | (.1939) | (.2336) |
| AIC | 6269.12 | 2384.53 |
| BIC | 6355.17 | 2452.30 |
| –2 Log-likelihood $\chi^2$ | 97.73** | 133.97** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Blog Model Results Using Alternative Number of Follower Metrics**

| Variable | UMV | Facebook Followers | UMV and Facebook |
|---|---|---|---|
| Intercept | 2.2241** | 2.4382** | 2.3222* |
| | (.1322) | (.1440) | (.1414) |
| Followers | -.0474 | .2364** | .2012+ |
| | (.0836) | (.0810) | (.1087) |
| Weekend post | -.1448 | -.2493 | -.1908 |
| | (.1528) | (.1661) | (.1672) |
| Type of campaign – awareness | -.5594** | -.7526** | -.7034** |
| | (.1396) | (.1437) | (.1449) |
| Blogger expertise (sum of credentials and education) | .3047** | .2116 | .2358 |
| | (.1167) | (.1544) | (.1521) |
| Functional value of post | .0677 | -.0430 | .0229 |
| | (.0776) | (.0821) | (.0834) |
| Hedonic value of post | -.0191 | -.0108 | .0202 |
| | (.0712) | (.0902) | (.0890) |
| Giveaway | 1.4748** | .5619** | .7004** |
| | (.1667) | (.1808) | (.1817) |
| Awareness × expertise interaction | .3054 | .4376+ | .4640+ |
| | (.2252) | (.2627) | (.2614) |
| Awareness × functional interaction | -.1660 | -.0215 | -.1076 |
| | (.1162) | (.1204) | (.1212) |
| Awareness × hedonic interaction | .0202 | .05133 | .0224 |
| | (.1185) | (.1357) | (.1336) |
| Awareness × giveaway interaction | -.5327+ | .3738 | .1687 |
| | (.2935) | (.3044) | (.3046) |
| Awareness × followers interaction | .1969 | .0996 | .1719 |
| | (.1283) | (.1216) | (.1603) |
| Inverse Mills ratio | .2322 | .1710 | .2349 |
| | (.3300) | (.3634) | (.3595) |
| Overdispersion (α) | 4.2213** | 4.3089** | 4.2460** |
| | (.1701) | (.1862) | (.1851) |
| AIC | 9041.47 | 7735.83 | 7591.79 |
| BIC | 9121.19 | 7813.89 | 7669.57 |
| –2 Log-likelihood $\chi^2$ | 249.42** | 108.96** | 104.68** |

Notes: Standard errors are in parentheses.
$^+$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Facebook Model Results Using Alternative Number of Follower Metrics**

| Variable | UMV | Facebook Followers | UMV and Facebook |
|---|---|---|---|
| Intercept | 1.3083** | 1.3921** | 1.3446** |
| | (.1793) | (.1817) | (.1829) |
| Followers | .2679** | .0046 | .0792 |
| | (.1114) | (.0785) | (.1202) |
| Weekend post | .6858** | .6846** | .6627** |
| | (.2003) | (.2118) | (.2142) |
| Number of Facebook posts | .4839** | .5444** | .5540** |
| | (.0807) | (.0824) | (.0856) |
| Type of campaign – awareness | .9302** | .7796** | .7413** |
| | (.1945) | (.1890) | (.1943) |
| Blogger expertise (sum of credentials and education) | -.3995** | -.3159+ | -.2975+ |
| | (.1413) | (.1733) | (.1743) |
| Functional value of post | .2010* | .1324 | .1334 |
| | (.0790) | (.0835) | (.0857) |
| Hedonic value of post | .0530 | .1446 | .1314 |
| | (.0898) | (.0969) | (.0965) |
| Giveaway | -.3081 | -.3895+ | -.3956+ |
| | (.1942) | (.2188) | (.2184) |
| Awareness × expertise interaction | -.1051 | -.1676 | -.1369 |
| | (.2510) | (.2818) | (.2786) |
| Awareness × functional interaction | -.2504* | -.2165+ | -.1994 |
| | (.1249) | (.1256) | (.1271) |
| Awareness × hedonic interaction | -.3122* | -.4605** | -.3989** |
| | (.1322) | (.1362) | (.1353) |
| Awareness × giveaway interaction | .0078 | .1861 | .1729 |
| | (.3285) | (.3427) | (.3450) |
| Awareness × followers interaction | -.0560 | .4278** | .3860* |
| | (.1715) | (.1264) | (.1763) |
| Inverse Mills ratio | .2980 | .0429 | .1571 |
| | (.3984) | (.4129) | (.4135) |
| Overdispersion (α) | 4.3790** | 3.9893** | 4.0132** |
| | (.1980) | (.1888) | (.1903) |
| AIC | 6449.60 | 5896.16 | 5857.98 |
| BIC | 6529.88 | 5973.95 | 5935.64 |
| –2 Log-likelihood $\chi^2$ | 260.72** | 233.13** | 226.95** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$. **Significant at $p < .01$.

## Alternative Engagement Metrics

| Variable | Blog Engagement: Blog post comments | Blog Engagement: Positive blog post comments | Facebook Engagment: Facebook post likes | Facebook Engagment: Facebook post Likes and Comments | Facebook Engagment: Facebook post Likes, Comments, and Shares |
|---|---|---|---|---|---|
| Intercept | 2.0403** | 1.2206** | 1.4032** | .9411** | .5882** |
| | (.1479) | (.1647) | (.1968) | (.1905) | (.1880) |
| Average number of followers (ln, Mean-Centered) | .3514** | -.0400 | .2055* | .19205* | .1838* |
| | (.0821) | (.1067) | (.0941) | (.0909) | (.0907) |
| Weekend post | -.1837 | .2311 | .7038** | .6750** | .7336** |
| | (.1641) | (.1804) | (.2168) | (.2053) | (.2028) |
| Number of Facebook posts | N/A | N/A | .5728** | .5050** | .4726** |
| | N/A | N/A | (.0891) | (.0830) | (.0809) |
| Type of campaign – awareness | -.2351+ | .9181** | .7416** | .7531** | .7616** |
| | (.1417) | (.1591) | (.1883) | (.1792) | (.1773) |
| Blogger expertise (sum of credentials and education) | -.1228 | -.4933 | .0253 | .0264 | .0042 |
| | (.2000) | (.3237) | (.2591) | (.2479) | (.2471) |
| Functional value of post | .0298 | .2925** | .0520 | .0025 | -.0123 |
| | (.0790) | (.0891) | (.0906) | (.0869) | (.0860) |
| Hedonic value of post | .2616** | .1763+ | .2215* | .2390* | .2596** |
| | (.0888) | (.0931) | (.1007) | (.0959) | (.0956) |
| Giveaway | .4526* | .3770+ | -.7840** | -.7930** | -.7744** |
| | (.1834) | (.2140) | (.2245) | (.2173) | (.2189) |
| Awareness × expertise interaction | .7283* | 1.0131** | -.4534 | -.4264 | -.2250 |
| | (.2911) | (.3753) | (.3393) | (.3229) | (.3179) |
| Awareness × functional interaction | -.1269 | -.3348** | -.1533 | -.0968 | -.0974 |
| | (.1185) | (.1366) | (.1308) | (.1227) | (.1231) |
| Awareness × hedonic interaction | -.2167 | .0717 | -.4824** | -.4782** | -.4971** |
| | (.1323) | (.1366) | (.1356) | (.1293) | (.1284) |
| Awareness × giveaway interaction | .4322 | -.0823 | .5312 | .5832+ | .6150+ |
| | (.3020) | (.3085) | (.3364) | (.3216) | (.3223) |
| Awareness × followers interaction | -.1413 | .4582** | .1457 | .1272 | .1153 |
| | (.1127) | (.1282) | (.1301) | (.1227) | (.1211) |
| Inverse Mills ratio | -.1255 | .3672 | .1255 | .1518 | .2168 |
| | (.3601) | (.3670) | (.4343) | (.4013) | (.3968) |
| Overdispersion (α) | 4.0632** | 1.5292** | 3.7449** | 3.3136** | 3.1867** |
| | (.1915) | (.1070) | (.1829) | (.1659) | (.1640) |
| AIC | 6662.87 | 2609.13 | 5581.87 | 4812.97 | 4364.24 |
| BIC | 6739.68 | 2670.23 | 5505.78 | 4888.86 | 4440.13 |
| –2 Log-likelihood $\chi^2$ | 100.64** | 107.09** | 221.91** | 215.36** | 214.64** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Blogger Profile Varimax Rotation Using the Reverse Code of Location Reference**

| Psychographic Variables | Expertise | Travel/Foodie | Persona | Lifestyle | Values |
|---|---|---|---|---|---|
| Religious | -0.13 | -0.32 | -0.03 | 0.22 | **0.65** |
| Professional reference | -0.18 | -0.23 | **0.71** | 0.07 | -0.03 |
| Blogger credential | **0.71** | 0.02 | 0.19 | 0.00 | -0.01 |
| Homeschool | 0.16 | -0.03 | -0.06 | **0.48** | 0.22 |
| Travel | -0.02 | **0.72** | 0.14 | -0.03 | -0.04 |
| Special needs | -0.15 | 0.00 | -0.01 | 0.07 | 0.12 |
| Technology/social media | 0.27 | 0.36 | **0.49** | -0.07 | 0.17 |
| Location reference (reverse-coded) | -0.67 | 0.17 | 0.21 | -0.10 | 0.06 |
| Political affiliation | 0.04 | 0.14 | -0.04 | -0.17 | **0.72** |
| Educational affiliation | **0.71** | 0.01 | 0.09 | 0.08 | 0.05 |
| Brand affiliation | 0.16 | 0.07 | **0.66** | -0.01 | -0.11 |
| Food & wine | -0.11 | **0.76** | -0.20 | 0.07 | -0.01 |
| Environmental affiliation | 0.07 | -0.15 | -0.05 | **0.60** | -0.23 |
| Health affiliation | -0.18 | 0.26 | 0.19 | **0.67** | 0.04 |

**Model Results Including Independent Variables in Stage 1 Model**

| Variable | Blog Post Comments | Facebook Post Likes |
|---|---|---|
| Intercept | 1.8546** | 1.4384** |
| | (.1530) | (.1990) |
| Average number of followers (ln, mean-centered) | .3054** | .2138* |
| | (.0863) | (.0966) |
| Weekend post | -.0865 | .7199** |
| | (.1743) | (.2162) |
| Number of Facebook posts | N/A | .5392** |
| | N/A | (.0883) |
| Type of campaign – awareness | -.2115 | .7939** |
| | (.1487) | (.1888) |
| Blogger expertise (sum of credentials and education) | -.0032 | .0182 |
| | (.2181) | (.2568) |
| Functional value of post | .0142 | .0393 |
| | (.0895) | (.0905) |
| Hedonic value of post | .2276* | .2233* |
| | (.0907) | (.1000) |
| Giveaway | .5057** | -.7664** |
| | (.1893) | (.2242) |
| Awareness × expertise | .5966+ | -.4605 |
| | (.3123) | (.3374) |
| Awareness × functional | -.1201 | -.1456 |
| | (.1283) | (.1305) |
| Awareness × hedonic | -.1609 | -.4904** |
| | (.1340) | (.1349) |
| Awareness × giveaway | .4555 | .4938 |
| | (.3111) | (.3362) |
| Awareness × followers | -.0435 | .1303 |
| | (.1177) | (.1303) |
| Inverse Mills ratio | .3681 | .1215 |
| | (.3287) | (.4039) |
| Overdispersion (α) | 3.9630** | 3.6915** |
| | (.1949) | (.1802) |
| AIC | 6124.91 | 5475.49 |
| BIC | 6200.29 | 5551.36 |
| –2 Log-likelihood $\chi^2$ | 96.94** | 218.63** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Blog Post Comments Model with Alternative Expertise Operationalization**

| Variable | Credentials and Education | Credentials Only | Education Only |
|---|---|---|---|
| Intercept | 2.0513** | 2.0488** | 2.0106** |
| | (.1486) | (.1487) | (.1440) |
| Average number of followers (ln, mean-centered) | .3582** | .3560** | .3576** |
| | (.0825) | (.0820) | (.0824) |
| Weekend post | -.1786 | -.1864 | -.1999 |
| | (.1641) | (.1645) | (.1644) |
| Type of campaign – awareness | -.2423+ | -.2477+ | -.1712 |
| | (.1427) | (.1428) | (.1387) |
| Blogger expertise (credentials) | -.2844 | -.2268 | N/A |
| | (.2672) | (.2533) | N/A |
| Blogger expertise (education) | .3350 | N/A | .1306 |
| | (.5952) | N/A | (.5631) |
| Functional value of post | .0312 | .0279 | .0397 |
| | (.0786) | (.0788) | (.0784) |
| Hedonic value of post | .2610** | .2627** | .2555** |
| | (.0885) | (.0888) | (.0886) |
| Giveaway | .4465* | .4488* | .4567* |
| | (.1834) | (.1837) | (.1838) |
| Awareness × giveaway | .4354 | .5530+ | .5843* |
| | (.3018) | (.2993) | (.2965) |
| Awareness × expertise (credentials) | .8425* | .9383* | N/A |
| | (.3964) | (.3820) | N/A |
| Awareness × expertise (education) | .3661 | N/A | .8191 |
| | (.7562) | N/A | (.7194) |
| Awareness × functional | -.1275 | -.1300 | -.1328 |
| | (.1182) | (.1184) | (.1179) |
| Awareness × hedonic | -.2200+ | -.1996 | -.2454+ |
| | (.1331) | (.1328) | (.1327) |
| Awareness × followers | -.1488 | -.1461 | -.1639 |
| | (.1130) | (.1127) | (.1130) |
| Inverse Mills ratio | -.1352 | -.1194 | -.0856 |
| | (.3600) | (.3604) | (.3601) |
| Overdispersion (α) | 4.0599** | 4.0726** | 4.0827** |
| | (.1914) | (.1919) | (.1922) |
| AIC | 6666.06 | 6664.91 | 6667.10 |
| BIC | 6753.11 | 6741.72 | 6743.90 |
| –2 Log-likelihood $\chi^2$ | 101.45** | 98.60** | 96.42** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Facebook Post Likes Model with Alternative Expertise Operationalization**

| Variable | Credentials and Education | Credentials Only | Education Only |
|---|---|---|---|
| Intercept | 1.4079** | 1.4355** | 1.3848** |
| | (.1964) | (.1965) | (.1916) |
| Average number of followers (ln, mean-centered) | .2017* | .2094* | .1977* |
| | (.0943) | (.0944) | (.0938) |
| Weekend post | .6945** | .6652** | .7425** |
| | (.2197) | (.2165) | (.2207) |
| Number of Facebook posts | .5787** | .5806** | .5724** |
| | (.0891) | (.0890) | (.0897) |
| Type of campaign – awareness | .7184** | .7133** | .7103** |
| | (.1898) | (.1904) | (.1828) |
| Blogger expertise (credentials) | -.1973 | -.1798 | N/A |
| | (.2929) | (.2926) | N/A |
| Blogger expertise (education) | .7524 | N/A | .7465 |
| | (.6471) | N/A | (.6500) |
| Functional value of post | .0578 | .0498 | .0609 |
| | (.0895) | (.0903) | (.0900) |
| Hedonic value of post | .2186* | .2098* | .2294* |
| | (.0990) | (.0996) | (.0990) |
| Giveaway | -.8617** | -.7967** | -.8503** |
| | (.2287) | (.2256) | (.2282) |
| Awareness × giveaway | .6004+ | .5141 | .5582+ |
| | (.3404) | (.3338) | (.3382) |
| Awareness × expertise (credentials) | -.3628 | -.4100 | N/A |
| | (.4209) | (.4114) | N/A |
| Awareness × expertise (education) | -.9258 | N/A | -1.1678 |
| | (.8210) | N/A | (.8139) |
| Awareness × functional | -.1582 | -.1485 | -.1768 |
| | (.1303) | (.1310) | (.1302) |
| Awareness × hedonic | -.4817** | -.4749** | -.4797** |
| | (.1344) | (.1350) | (.1335) |
| Awareness × followers | .1434 | .1310 | .1469 |
| | (.1309) | (.1308) | (.1305) |
| Inverse Mills ratio | .1698 | .0945 | .1663 |
| | (.4346) | (.4325) | (.4367) |
| Overdispersion (α) | 3.7350** | 3.7420** | 3.7503** |
| | (.1825) | (.1828) | (.1831) |
| AIC | 5507.38 | 5505.14 | 5506.90 |
| BIC | 5592.99 | 5581.23 | 5582.99 |
| –2 Log-likelihood $\chi^2$ | 224.31** | 222.56** | 220.79** |

Notes: Standard errors are in parentheses.
$^+$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

**Post Comments and Post Likes per Follower**

| Variable | | Blog Post Comments per Follower (ln of average Twitter, Facebook) | Facebook Post Likes per Facebook follower |
|---|---|---|---|
| Intercept | | .0865 | -6.1090** |
| | | (.1202) | (1.2426) |
| Weekend post | | -.1858 | -.0329 |
| | | (.1421) | (.9668) |
| Number of Facebook posts | | N/A | .0562 |
| | | N/A | (.1636) |
| Type of campaign – awareness | | -.6915** | -.1660 |
| | | (.1257) | (.8302) |
| Blogger expertise (sum of credentials and education) | | .1515 | 2.1625 |
| | | (.1181) | (2.2305) |
| Functional value of post | | -.0417 | .2830 |
| | | (.0666) | (.3938) |
| Hedonic value of post | | .0430 | -1.2849** |
| | | (.0695) | (.3987) |
| Giveaway | | .6298** | -2.9207 |
| | | (.1425) | (2.8647) |
| Awareness × expertise | | .4345* | 1.7124 |
| | | (.1920) | (2.6167) |
| Awareness × functional | | -.0816 | -.4953 |
| | | (.1022) | (.6010) |
| Awareness × hedonic | | -.0342 | 1.0867+ |
| | | (.1097) | (.6288) |
| Awareness × giveaway | | .3841 | 3.0945 |
| | | (.2441) | (3.1071) |
| Inverse Mills ratio | | .4315 | 4.9438+ |
| | | (.3068) | (2.7502) |
| Overdispersion (α) | | 2.4824** | 1.8949** |
| | | (.1438) | (.8002) |
| AIC | | 4094.43 | 142.40 |
| BIC | | 4162.84 | 210.47 |
| –2 Log-likelihood $\chi^2$ | | 139.99** | 28.66** |

Notes: Standard errors are in parentheses.
$^+$Marginally significant at $p < .10$.
*Significant at $p < .05$
**Significant at $p < .01$.

## Gaussian Copula Model Specification

| Variable | Blog post comments (ln) | Blog post comments (standardized ln) | Facebook post likes (ln) | Facebook post likes (standardized ln) |
|---|---|---|---|---|
| **Selection Marginal Model** | | | | |
| Intercept | -2.4691** | -2.4691** | -2.5801** | -2.5801** |
| | (.0231) | (.0231) | (.0261) | (.0261) |
| Similar Blogger Choice | 1.3183** | 1.3183** | 1.3920** | 1.3920** |
| | (.0350) | (.0350) | (.0375) | (.0375) |
| Travel/Foodie | .0689** | .0689** | .0438* | .0438* |
| | (.0176) | (.0176) | (.0190) | (.0190) |
| Persona | .0185 | .0185 | .0325+ | .0325+ |
| | (.0178) | (.0178) | (.0191) | (.0191) |
| Lifestyle | -.0062 | -.0062 | -.0070 | -.0070 |
| | (.0164) | (.0164) | (.0175) | (.0175) |
| Values | -.0000 | -.0000 | .0026 | .0026 |
| | (.0196) | (.0196) | (.0205) | (.0205) |
| **Dependent Variable Marginal Model** | | | | |
| Intercept | 1.7428** | -.2668* | 1.4853** | -.0994 |
| | (.1963) | (.1220) | (.2751) | (.1755) |
| Average number of followers (ln, mean-centered) | .2621** | .1628** | .0931 | .0594 |
| | (.0622) | (.0386) | (.0865) | (.0552) |
| Weekend post | -.1037 | -.0644 | .3676* | .2345* |
| | (.1299) | (.0807) | (.1775) | (.1133) |
| Number of Facebook posts | N/A | N/A | .0220 | .0140 |
| | N/A | N/A | (.0442) | (.0282) |
| Type of campaign – awareness | .0145 | .0090 | .6514** | .4156** |
| | (.1203) | (.0747) | (.1545) | (.0986) |
| Blogger expertise (sum of credentials and education) | -.0054 | -.0034 | -.1436 | -.0916 |
| | (.1645) | (.1022) | (.2317) | (.1478) |
| Functional value of post | -.0644 | -.0400 | -.0950 | -.0606 |
| | (.0633) | (.0394) | (.0935) | (.0597) |
| Hedonic value of post | .2576** | .1600** | .2360 | .1506* |
| | (.0663) | (.0412) | (.0947) | (.0604) |
| Giveaway | .2304 | .1431 | -.2746 | -.1752 |
| | (.1428) | (.0887) | (.2169) | (.1384) |
| Awareness × expertise | .5226* | .3246* | -.1060 | -.0676 |
| | (.2324) | (.1444) | (.3165) | (.2020) |
| Awareness × functional | .0652 | .0405 | .0575 | .0367 |
| | (.0946) | (.0588) | (.1267) | (.0809) |
| Awareness × hedonic | -.1960+ | -.1218+ | -.3115* | -.1988* |
| | (.1010) | (.0627) | (.1290) | (.0823) |
| Awareness × giveaway | .1979 | .1229 | .0373 | .0238 |
| | (.2169) | (.1347) | (.3143) | (.2006) |
| Awareness × followers | -.0611 | -.0379 | .1495 | .0954 |
| | (.0952) | (.0592) | (.1167) | (.0744) |
| **Parameter Estimates and Fit Statistics** | | | | |
| ln(sigma) | .2414** | -.2347** | .4455** | -.0037 |
| | (.0266) | (.0266) | (.0286) | (.0286) |
| Theta | .0094 | .0094 | -.0055 | -.0055 |
| | (.0715) | (.0715) | (.0765) | (.0765) |
| Kendall's Tau | -.0060 | -.0060 | .0035 | .0335 |
| | (.0455) | (.0455) | (.0487) | (.0487) |
| LR Test of Independence | .0170 | .0170 | -.0050 | .0050 |
| AIC | 8078.29 | 7404.22 | 7198.41 | 6650.31 |
| BIC | 8258.44 | 7584.36 | 7387.08 | 6838.98 |
| Wald $\chi^2$ | 1432.25** | 1432.25 | 1388.48** | 1388.48** |

Notes: Standard errors are in parentheses.
$^+$Marginally significant at $p < .10$.
*Significant at $p < .05$.
**Significant at $p < .01$.

# APPENDIX B

## Varimax Factor Pattern Rotation for Blogger Psychographic Variables

| Summary Statistics | Alpha | M | SD |
|---|---|---|---|
| Credential and education | 0.5061 | 0.41 | 0.65 |
| Credential, education, location | 0.5446 | 1.02 | 0.67 |

**Summary Table of Effect Sizes**

| Variable | Blog Post Comments | Facebook Post Likes |
|---|---|---|
| Intercept | 7.6932** | 4.0683** |
| | (1.1377) | (.8008) |
| Average number of followers (ln, mean-centered) | 1.4210** | 1.2282* |
| | (.1166) | (.1155) |
| Weekend post | .8322 | 2.0214** |
| | (.1366) | (.4382) |
| Number of Facebook posts | N/A | 1.7732** |
| | N/A | (.1580) |
| Type of campaign – awareness | .7905+ | 2.0993** |
| | (.1120) | (.3952) |
| Blogger expertise (sum of credentials and education) | .8844 | 1.0256 |
| | (.1769) | (.2657) |
| Functional value of post | 1.0303 | 1.0533 |
| | (.0814) | (.0954) |
| Hedonic value of post | 1.2990** | 1.2480* |
| | (.1153) | (.1256) |
| Giveaway | 1.5724* | .4566** |
| | (.2884) | (.1025) |
| Awareness × expertise | 2.0717* | .6354 |
| | (.6030) | (.2156) |
| Awareness × functional | .8808 | .8579 |
| | (.1044) | (.1122) |
| Awareness × hedonic | .8052 | .6173** |
| | (.1065) | (.0837) |
| Awareness × giveaway | 1.5406 | 1.7009 |
| | (.4653) | (.5723) |
| Awareness × followers | .8682 | 1.1568 |
| | (.0978) | (.1505) |
| Inverse Mills ratio | .8820 | 1.1337 |
| | .3176 | (.4924) |
| Overdispersion (α) | 4.0632** | 3.7449** |
| | (.1915) | (.1829) |
| AIC | 6662.87 | 5505.78 |
| BIC | 6739.68 | 5581.87 |
| –2 Log-likelihood $\chi^2$ | 100.64** | 221.91** |

**Main Effects Model Results Table**

| Variable | Blog post comments | Facebook post likes |
|---|---|---|
| Intercept | 2.2660** | 1.4152** |
| | (.1421) | (.1850) |
| Average number of followers (ln, Mean-Centered) | .2008** | .3005** |
| | (.0612) | (.0685) |
| Weekend post | -.3026+ | .5486** |
| | (.1674) | (.2087) |
| Number of Facebook posts | N/A | .5052** |
| | N/A | (.0809) |
| Type of campaign – awareness | -.5088** | .8897** |
| | (.1210) | (.1579) |
| Blogger expertise | .4282** | -.4050** |
| | (.1248) | (.1374) |
| Functional value of post | -.1181+ | .0054 |
| | (.0636) | (.0632) |
| Hedonic value of post | .0466 | -.0506 |
| | (.0663) | (.0669) |
| Giveaway | .8097** | -.2920+ |
| | (.1440) | (.1610) |
| Inverse Mills ratio | .3216 | .3195 |
| | (.3540) | (.4154) |
| Overdispersion (α) | 4.3469** | 3.9567** |
| | (.1921) | (.1862) |
| AIC | 7381.82 | 5887.30 |
| BIC | 7433.43 | 5940.59 |
| –2 Log-likelihood $\chi^2$ | 101.81** | 212.16** |

Notes: Standard errors are in parentheses.
$^{+}$Marginally significant at *p* < .10.
*Significant at *p* < .05.
**Significant at *p* < .01.

**Table of Sentiment Measure Correlations**

| Variables | Positive Emotion (LIWC) | Negative Emotion (LIWC) | Functional | Hedonic |
|---|---|---|---|---|
| **Positive emotion (LIWC)** | 1 | 0.7362** | 0.0581 | 0.1107** |
| **Negative emotion (LIWC)** | | 1 | 0.02333 | 0.0788* |
| **Functional** | | | 1 | 0 |
| **Hedonic** | | | | 1 |

*Significant at $p < .05$.
**Significant at $p < .01$.

## APPENDIX C

Stimuli Used in Pretest and Study 3

Negative Leader:

**Alex**
40 friends
222 reviews
40 photos

First to Review

Awful, awful experience here. Employees were too busy laughing and goofing around in the back to even come and take care of the customers. The food took forever to arrive at our table. Ordered a dinner salad which was missing an ingredient and the portion was quite small (which is why I was able to spot a missing ingredient). Spoke to the waitress, who informed me that they were out the ingredient. They should have told me before I ordered! Very disappointed and frustrated!!

Negative Follower:

**Elliot**
42 friends
224 reviews
42 photos

Second to Review

I made the mistake of coming here after work. It was early, not packed at all. Actually pretty empty. Waited about 10 minutes for a waiter just to come to my table. Finally, ordered everything at one time, because I did not want to wait forever for him to come back. Waited about 30 minutes for my soup and appetizer, our waiter walked by us several times, not telling us a thing. Finally, after almost an hour, our food arrived and it was not worth the long wait and frustration. The experience here was absolutely terrible and the food wasn't great either!

Positive Leader:

Jamie
44 friends
220 reviews
40 photos

First to Review

I came here for dinner last night. The service was amazing. My poor server was swamped with tables (having been a server myself I know how tough that can be), but he remained calm, professional, and very attentive. Good food, nice environment, friendly staff, I will definitely come back and enjoy some more of this place.

Positive Follower:

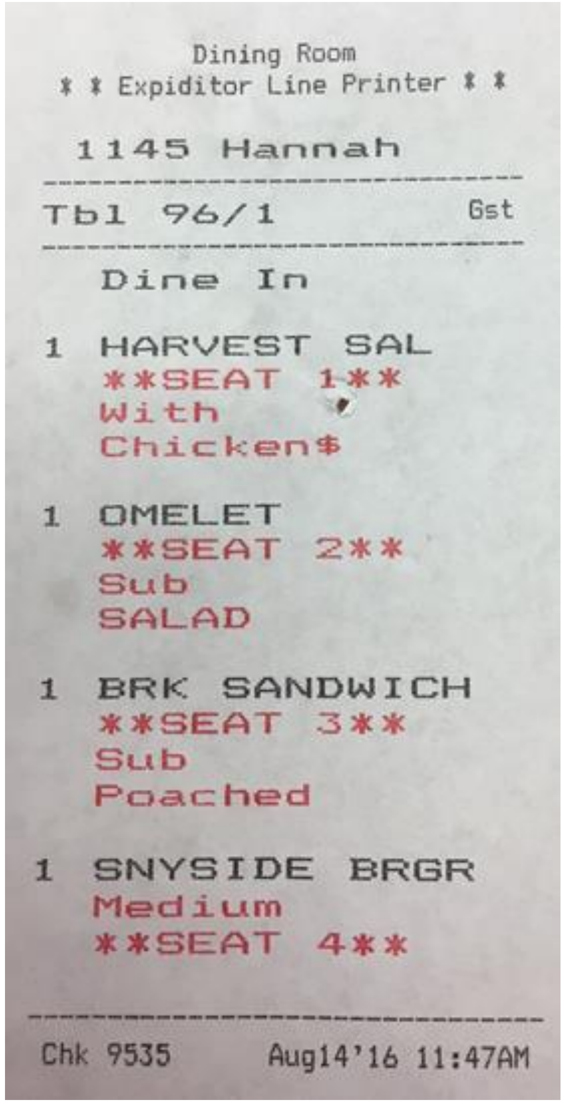
Sam M
42 friends
224 reviews
40 photos

Second to Review

This is my new favorite restaurant. OMG the food was amazingly delicious. I ordered the iced tea to drink and soup as an appetizer - yum!! The grilled chicken and the salad were both great! So so yummy! The menu is very diverse with tasty options. This place is clean and affordable. I love this place!!! I'll be back soon!!

**APPENDIX D**

Example Receipt



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