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朋友的朋友如何影響網路購買意願：兩個 Facebook 研究

How Friends' Friends Influence Online Purchase Intentions: Two Facebook Studies

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摘要

本文對社交網站傳遞的產品品質信號進行實證。我們以「朋友」和「讚」的線索來衡量它們對產品品質認知的影響，並同時研究熟悉度、認知風險和評論效價的調節作用。透過兩個 Facebook 實驗，我們首先比較了朋友、朋友的朋友、和廣告所提供的資訊之影響。結果表明，品質認知會受到社交信號的影響而帶來購買意願。「朋友」線索的影響受到熟悉度和風險的正向調節。然而，「讚」對品質認知的影響在不同的熟悉度和風險中沒有明顯的差異。接著，我們區分正面和負面評論以探討資訊效價的影響。結果顯示，在負面評論下，朋友和衍生朋友的線索所產生的信號之影響並沒有差異；「讚」的數量也是一樣的結果。亦即，對負面評論的評斷會遮蓋掉好友類型和評級數量的影響。

關鍵詞：社交信號、Facebook 按讚、朋友的朋友、負面評價、產品認知品質

Abstract

This study examines the signals of product quality transmitted on social network sites. We use the cues friend and like as measurements to determine their influence on perceived product quality and the moderating role of familiarity, perceived risk, and review valence. The hypotheses were tested using two Facebook field experiments. We first compared the effects of information provided by friends, friends of friends, and advertisements. The results indicate that social signals affect perceived product quality, which produces intentions to purchase. The effect of friend cues is positively moderated by perceived familiarity and risk. Nevertheless, like does not make a noticeable difference on perceived quality for varying perceived familiarity and risk. We then studied the effect of information valence by differentiating between positive and negative reviews. The results indicate that the power of signals produced by friends' and derived friends' cues does not differ under negative review situations; the same result was found for like volume. The judgment of negative reviews overshadows both friendship type and rating volume effects.

Keywords: Social Signal, Facebook Like, Friend of Friend, Negative Review; Perceived Product Quality

1. Introduction

An increasing number of individuals participate in online activities via social network sites (SNSs), such as Facebook, which enable users to communicate or provide additional information about the content other users post (Karahasanović et al., 2009). Studies have shown that others can heavily influence online users' behaviors and attitudes (Centola, 2010; Liang et al., 2011; Liang & Turban, 2011; Liang et al., 2015). In recent years, due to the popularity of SNSs, such as Twitter, Facebook, and Instagram (IG), many social signals can be measured in practice (friends, likes, comments, shares, followers, etc.). To achieve better search results, Google began integrating social signals into its algorithms on SNSs. One common strategy for assessing the credibility of online recommendations is to consider social cues (Metzger et al., 2010). Researchers believe that social cues on SNSs are critical for consumers looking for signals when making decisions.

Drawing on signaling theory (Spence, 1973, 1974), this study shows how various cues with different social signals on SNSs affect consumers' cognition and purchase behavior. Previous studies have demonstrated that signals influence how consumers judge the quality of a product. When the available product information is incomplete, consumers often use readily available, easily assessable clues to evaluate product quality (Zeithaml, 1988). Signaling theory provides an appropriate analytical framework on how consumers can reduce uncertainty and obtain information about the quality of a product in the process of exchange or interchange (Kirmani & Rao, 2000).

In this study, we show online *friend* and *like* cues as signals of perceived product quality. Drawing from social signal theory, we maintain that the connection between friends can transmit trust signals. Moreover, we divide friends into two different types by distinguishing between one and two steps away from the user. While studies of strong ties abound in the context of social commerce, few have examined the effect of weak ties (e.g., friends of friends). Previous studies have shown that information from direct online friends has high diagnosticity and, therefore, promotes subsequent purchases (Wang & Chang, 2013). This study contributes to the extant literature by including the signals' indirect effects. This

approach echoes Salehan et al.'s (2017) classification of social motivation on SNS, that vertical social motivation refers to close and strong ties with established ties, while horizontal social motivation refers to developing weak relationships with those who share common interests.

Our research extends the trust transfer between consumers and friends to explore whether the trust generated between consumers and derived friends still influences consumers' attitudes toward products. Since trust generally comes from people sharing similar values and proximity, we believe that the social relationship between a friend and a derived friend will also develop trust with that derived friend. Thus, in Study 1, we fill the research gap by exploring whether a derived friend's attitude and comments concerning a product also affect a consumer's perceived product value, especially on social commerce platforms.

Regarding the moderators, we explored whether the effects of these social signals differ for different levels of perceived product familiarity and risk. Consumers may vary in their ability to process information (Henry, 1980); therefore, social signal influences could differ from person to person. We maintain that the two signals may still be subject to two conditions: familiarity and perceived risk of the product. Additionally, since information's positive or negative nature affects individual responses (Ilgen et al., 1979), we add the effect of information valence as the third condition while manipulating cues of *friend* and *like*. Therefore, the impact of signals on perceived product quality likely differs across information valence, which is another research gap of the field.

This paper also expands previous research on the impact of information valences on decision-making on online social networks. Past research has pointed to the different effects of negative and positive information on consumers' decision-making processes (Kim et al., 2018; Li et al., 2019). This study specifically examines the moderating effect of different information valences (positive vs. negative reviews) while manipulating other signals of product quality. When consumers face a negative review, they are subject to assessing the product's quality more carefully and, therefore, might be more diagnostic. We conducted a second field experiment on Facebook to explore these issues and determine how information valences interact with friend types and *like* volumes (Study 2). The finding shows that

compared to positive reviews, which encourage consumers to distinguish between friend types and *like* volumes, negative reviews overshadow the role of these additional signals; they diminish the impact of rating volume and friend types.

The remainder of this paper is organized as follows. First, we summarize previous literature to contextualize our study and hypotheses. Second, we describe our research method and conduct field experiments to gather empirical data. Third, we analyzed the result and findings and included a discussion, and finally, we conclude with implications for scholars and managers.

2. Theoretical Background and Hypotheses Development

2.1 Signaling Theory and Social Signals

The importance of social-based information is increasing in convincing customers of product quality. Therefore, research on the signals of social-based information has begun to emerge. For example, Utz et al. (2012) suggest that online reviews, as opposed to assurance seals or general reputation, are more important indicators of an online store's trustworthiness. When asymmetric information exists, sellers likely possess a thorough knowledge of their product quality, whereas prospective buyers do not often have such knowledge. In such scenarios, sellers can send appropriate signals to buyers, and buyers can use them to shape their perceptions of quality and risk (Akerlof, 1970; Spence, 1973; Rao et al., 1999; Kirmani & Rao, 2000). To this end, signaling theory is widely used in various fields to analyze how one side receives and interprets the quality signals sent by the other side.

A vast body of empirical research examines the influence of various signals. Previous research on perceptions of product quality focused on the impact of different cues, such as reputation, price, and advertising. Furthermore, in the e-commerce context, researchers have examined website features as signals of quality and trustworthiness. Previous studies have shown that consumers' decision-making processes rely heavily on word-of-mouth (WOM) (Chu & Kim, 2018), social presence (Lu et al., 2016), information sharing (Bugshan & Attar,

2020), and referrals (Gorner et al., 2013; Kim & Kim, 2018). From a network perspective, people are more likely to follow other trustworthy buyers through contagion and observational learning (Xiao et al., 2015). With the support of third-party infomediaries, consumers can reduce perceived product uncertainty (Bai et al., 2015). Therefore, consumers' interactive behavior significantly shapes social commerce's value perceptions and purchasing decisions.

Social influences provide the information and motivation needed for developing new attitudes and adapting to new behaviors. Many consumers are influenced by other people's attitudes and behaviors (Burnkrant & Cousineau, 1975; Aronson & Aronson, 2018) because they observe others' behaviors and imitate them in subsequent conversations. Some studies note that when people seek information, they prefer to turn to others (Mintzberg, 1973; Allen, 1977). Consequently, consumers may rely on customer recommendations rather than marketer advertising (Biyalogorsky et al., 2001). To this end, WOM recommendations may play an essential role in decision-making (East et al., 2005).

Interpersonal persuasion and conformity shape consumer opinions significantly. The attitudes exhibited by others in an interacting social environment are likely to affect individuals highly involved in social networks in various ways. Cialdini's (2001) study of social proof states that persuasion is particularly useful when it comes from peers; individuals rely on those around them for cues about perceiving and acting. White & Simpson (2013) also suggest that social norms can sustainably foster intentions and behaviors by reflecting on others' behavior. As a result, information on SNSs is increasingly critical in forming consumer attitudes. Metzger et al. (2010) suggest that analyzing social cues can be helpful when the credibility of online information is uncertain. Thus, we advocate that social cues from SNS can be critical signals in shopping decisions.

2.2 Friend and Friend of Friend

When consumers do not know whether a product and recommendations can be trusted, they may take cues from social interactions on SNS. These cues include user-generated content and posts or advertising made by companies for their brands. Although cues from company-generated content on SNS posts signal trust about

attractiveness and popularity (Yang et al., 2020), previous studies note that consumers perceive advertising as more manipulative than informative (Mehta, 2000). Advertisers may have a profit motive, whereas friends and derived friends normally do not. Advertising credibility could be questioned as "cheap talk," increasing consumer skepticism. As a result, more and more studies focus on user-generated content. These studies explore whether consumer trust in other consumers, parties, or members could be transferred to consumer trust in products (Cheng et al., 2019), brands (Liu et al., 2018), and even firms (Ng, 2013), leading to subsequent purchase intentions.

However, consumers face the problem of false information regarding cues generated by these other consumers, including the inability to recognize the authenticity of their identities. While consumers widely use online reviews in their decision-making process, consumers may perceive these individuals as being manipulated by marketers (Kim et al., 2013; Ensing, 2014). There have been several documented cases of marketers posting positive reviews on their own products or negative reviews against a competitor. Therefore, for trust reasons, the information provided by consumers' personal networks, including signals from online friends, plays a constructive role in screening and filtering information. Because an individual's social network information is not easily manipulated, social network-based signals are a powerful tool for assessing products and/or vendors. In other words, consumers' attitudes are strongly influenced by their online friends (Centola, 2018). In this way, we can contribute to the theoretical implications of product quality signals by using *friend* cues. Therefore, we examine the influence of online friends as signals on consumers' purchase decisions.

People on SNS may see information about friends of friends, connect with those people, and be influenced by them (Shih, 2010). We refer to these characters as *derived friends*, i.e., if C is a friend of B and B is a friend of A, then C is a derived friend of A. It was difficult to identify friends of friends before the emergence of SNSs. However, SNSs made it possible for users to discover many different connections between people. Thus, we exploit the advantage that SNSs allow people to efficiently connect with their derived friends to explore the various effects of these clues on perceived quality.

For the friends of the customers' friends (derived friends), this study considers trust transfer as an indirect product of social signaling. Trust usually comes from shared values and proximity; thus, we believe that the relationships between the customer and friends will lead the customer to transfer prior trust to a derived friend. For example, suppose A trusts B and B trusts C. Then A will likely transitively trust C if C mentions B during contact with A. Figure 1 illustrates this idea.

In a network, everyone can spread information; however, people tend to be persuaded by credible information, and information from intimates is considered more reliable and trustworthy than that from acquaintances (Rogers, 2003). Based on this, we suggest that positive information from a derived friend is more likely to be viewed as less valuable than that from a close friend. People may perceive the quality of information from their derived friends to be lower than that of their direct friends.

This study enlisted a control group to receive the same advertising information. As mentioned earlier, there are doubts about companies' possible advertising manipulation. We maintain that consumers on SNSs may trust advertisers less than derived friends because advertisers do not typically have friendships with consumers. Consequently, we suggest that positive information from derived friends influences perceived product quality more than advertising information.

Hypothesis 1a*: Consumers perceive a higher level of product quality in response to recommendations and information provided by friends than recommendations and information provided by derived friends.*

Hypothesis 1b*: Consumers perceive a higher level of product quality in response to recommendations and information provided by derived friends than information provided by advertising.*

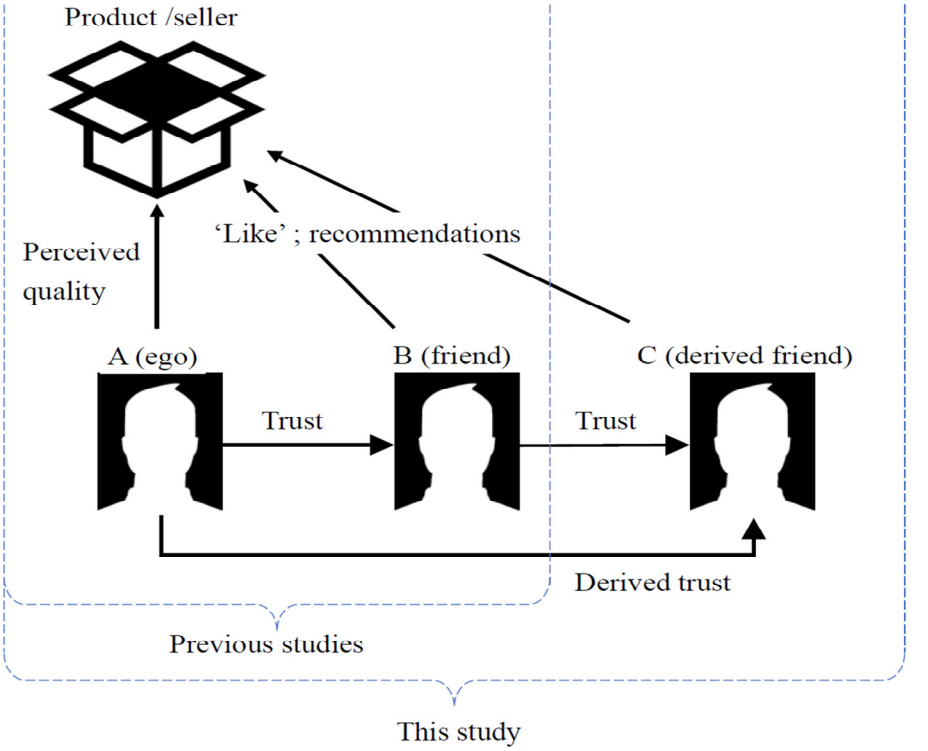


Figure 1. Signaling trust among friends

Data source: this research

2.3 Like Volumes

Recommendations have long been direct and intuitive user-generated signals about product quality. On SNS platforms, clicking *like* provides a convenient way for consumers to send signals that directly reflect the level of user-perceived popularity. Proliferating social media, such as Facebook, makes it possible to examine the influence of customer engagement, conformity, and rating volume in a real-world social network. Most social networks offer an easy way for users to share positive reactions to an item within the network. For example, Facebook enables users to *like* information with just one click of a button. To strengthen the status of *likes* as a crowd-based signal and their influence in the community, Facebook provides available metrics on the total number of *likes*. Based on their prevalence and the accessibility of the metrics described above, this paper selected the number of *likes* as the primary crowd-based signal.

Studies have determined that user rating quantity (volume) is a significant reference for consumers. For example, drawing upon social capital theory and strength of weak ties, Phua & Ahn's (2016) research on Facebook brand pages shows a significant relationship between the number of *likes* and consumers' attitudes, trust, and purchase intentions. When the quality of a product is uncertain, the number of ratings is more manageable for consumers to understand and digest. Therefore, consumers often use ratings directly as a proxy for quality popularity. Moreover, volume informs awareness and may influence users' attitudes; thus, several studies have identified volume as the most significant predictive factor for creating positive consumer attitudes (Chevalier & Mayzlin, 2006; Liu, 2006; Duan et al., 2008). Thus, *likes* offer an alternative form of "electronic word of mouth" and create new possibilities for identifying quality signals influencing purchase behavior.

Consumer decisions depend on the number of social reactions around them. The majority opinion of consumers' social groups influences purchasing decisions; many people thinking alike are perceived as more persuasive (Granovetter & Soong, 1988). Volume often leads to conformity, which, for this study's purpose, is a situation in which the consumer observes and makes a decision based on the intentions of other individuals. The number of others making decisions and taking action determines conformity (Granovetter & Soong, 1988). The pressure to conform arises when consumers judge a product's true quality based on others' opinions and decisions. The more people support a recommendation, the less perceived risk in taking the information as accurate, and the greater the trust placed in the product. That is to say, information that several people have *liked* a product or have recommended will heighten perceived product quality. Thus, we maintain that the more *likes* a product accrues, the better its quality in users' eyes. The hypotheses and the research framework are shown below.

Hypothesis 2*: Consumers perceive a higher level of product quality in response to recommendations and information with high like volumes than recommendations and information with low like volumes.*

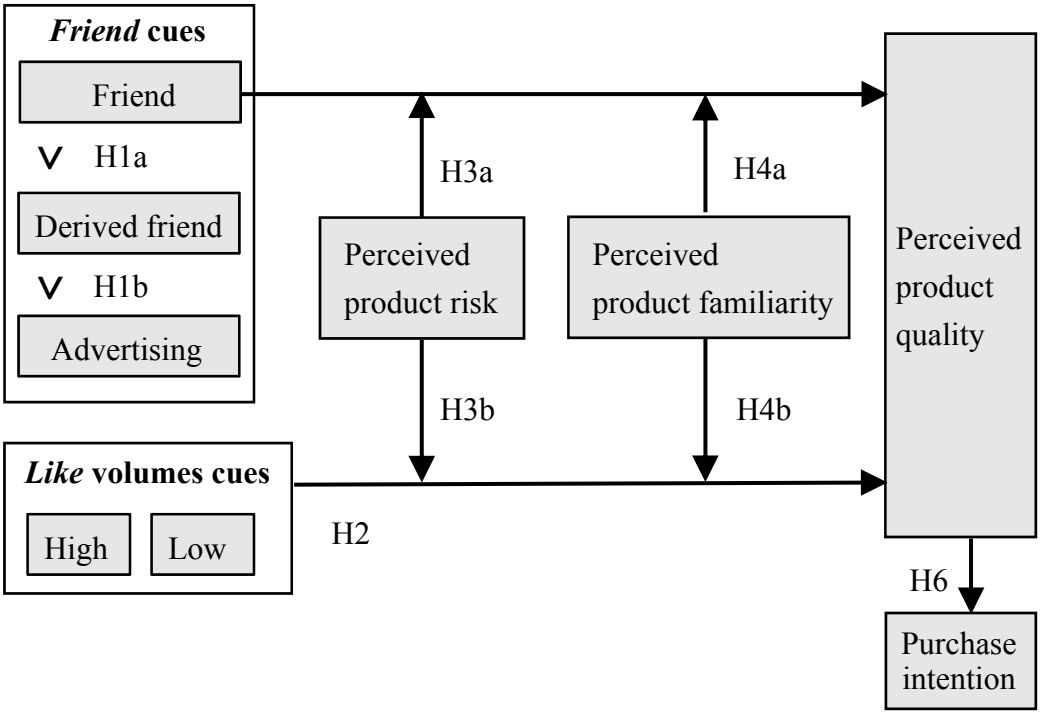


Figure 2. Research framework: Study 1

Data source: this research

2.4 Moderating Role of Perceived Product Risk

Researchers have long focused on the important role of product risk as a determinant of buyer action (Bettman, 1973; Dowling & Staelin, 1994; Harris et al., 2016; Sarkar et al., 2020). A customer exposed to indecision may pursue uncertainty reduction strategies in using signals to make choices (Jacoby et al., 1994). When the consequences of a decision become weighty, buyers tend to lean on additional guidance, in the form of WOM messages, advertisements, and advice from friends, to assuage feelings of doubt and indecision. In such cases, they are expected to find out more about the product; consequently, they may be more dependent on signals to establish confidence regarding their course of action (Zhang & Li, 2006).

However, when disadvantageous outcomes are not expected, signals will less likely influence consumers as there is no fear of possible undesirable consequences (Lian & Lin, 2008). As a result, we hypothesize that risk positively moderates the

relationship of *friend* cues and *like* volumes with perceived product quality and will be stronger in situations of high product risk than in those of low product risk.

Hypothesis 3a*: The effect on product quality, as perceived by consumers, of friends' cues is greater for those who see their purchase as risky than those who think that little risk is involved.*

Hypothesis 3b*: The effect on product quality, as perceived by consumers, of like volumes is greater for those who see their purchase as risky than those who think that little risk is involved.*

2.5 Moderating Role of Perceived Product Familiarity

When consumers are not familiar with a product, they use signals from others as clues to speculate whether the product quality is trustworthy (Yang et al., 2020). In most cases, it is easier for consumers to understand signals than to evaluate the products themselves because of the subject expertise this requires. So, they typically have greater confidence in their understanding of the signals than their knowledge of the products (Richardson et al., 1994). Consumers with less knowledge of a product rely more on signals because of this lack of understanding, which would allow them to choose based on the product's actual characteristics (Rao & Monroe, 1988). Accordingly, most consumers focus more on extrinsic than intrinsic characteristics, except when they undertake a customary purchase or are confident about their assessment ability to assess a product.

In contrast, consumers well acquainted with a product will have appropriately founded views regarding the products they intend to buy (Maheswaran, 1994; Maheswaran et al., 1996; Kuusela et al., 1998; Kardes et al., 2001; Siu & Wong, 2002; Harris et al., 2016). Therefore, signals play a more important role for consumers not well acquainted with a product, as they have little to base their purchasing decisions upon, except for signals, such as trust and product approval. As a result, it appears reasonable to assume that product familiarity also moderates the relationship that *friend* and *like* volumes signals have with perceived product quality. It will be stronger for consumers unknowledgeable about the products and weaker for knowledgeable consumers.

Hypothesis 4a*: The effect on product quality, as perceived by consumers, of friend cues is greater for those with low self-professed familiarity with the product than for those with high self-professed familiarity.*

Hypothesis 4b*: The effect on product quality, as perceived by consumers, of like volumes is greater for those with low self-professed familiarity with the product than for those with high self-professed familiarity.*

2.6 Moderating Role of information Valence

Several studies have indicated a positive relationship between reviews and consumer behavior (Park et al., 2007; Hong et al., 2017; Kim et al., 2018). Nevertheless, other studies show that readers feel that negative reviews deserve the same attention as positive reviews (Wang et al., 2015). Furthermore, a negative review may register more with readers than a positive one (Cui et al., 2012). For example, Basuroy et al. (2003) demonstrated that negative reviews damaged a movie's box office performance more than the degree to which positive reviews contributed. Another study by Chevalier & Mayzlin (2006)—on the degree to which consumer reviews influenced related book sales at Amazon.com and Barnesandnoble.com—found that 1-star reviews may more strongly affect sales figures than 5-star reviews. Negative reviews help more and are more diagnostic than positive reviews when classifying a product's quality and performance (Bhandari & Rodgers, 2018). Accordingly, this study assumes that customers' perceptions of quality are subject to other customers' valence types of engagement.

Specifically, we maintain that the two kinds of friendship affect perceived product quality differently when reviews are positive but not negative. The same pattern is expected in the differing effects associated with *like* volumes. There are two reasons for this. First, such asymmetry can be expected because negative product reviews are largely considered characteristic of low-quality products. In contrast, positive reviews indicate both low- and high-quality reviews. When presented with positive reviews, consumers search for additional information to help make purchase decisions. However, in the case of negative reviews, consumers have less reason to search for additional information to judge product quality because

negative reviews contain product failure information. The impact of this information on their choices is systematically stronger than any positive information they may find, which is objectively equivalent (Skowronski & Carlston, 1989). This suggests that when the message is positive, people will focus more on signals to help them judge the product quality. In contrast, people do not focus on signals when the message is negative because negative reviews alone are considered diagnostic. As a result, perceived product quality will be affected by *friend* cues and *like* volumes more strongly with positive reviews than negative ones.

Second, according to the elaboration likelihood model of persuasion, attitude change is described by a dual-route process (Petty & Cacioppo, 1986). Since overall ratings lack further narration, consumers cannot judge how reviewers reach conclusions, causing the persuasion process to follow a low-level elaboration route. In contrast, textual comments contain more information and drive consumers to spend extended time reading, thinking, and paying attention. Consumers seek more proactive thinking to form their own opinions (whether for or against a comment). In contrast to a simple inference based on volume quantity, persuasion results from textual comments that follow a route of high-level elaboration. However, readers have greater perceptual vigilance for negative information since negative reviews are often specifically related to consumers' economic or mental losses. Therefore, they will more likely analyze, judge, and establish their own subjective opinions. Once consumers form these personal opinions, perceived product quality is substantially biased, causing final product awareness to lose relevance with its information source. In other words, a subsequent escalation of commitment, created while judging negative reviews, overshadows the impact of rating volume and types of friends. We constructed a separate study to test their effects to address these complex relationships. The hypotheses and the research framework are shown below.

Hypothesis 5a*: A positive review provided by a friend will create a higher perceived product quality than a positive review provided by a derived friend.*

Hypothesis 5b*: Negative reviews provided by a friend and a derived friend do not create significantly different product quality perception.*

Hypothesis 5c*: A positive review supported by high like volumes will create higher perceived product quality than a positive review supported by low like volumes.*

Hypothesis 5d*: A negative review supported by high like volumes and one supported by low like volumes does not create significantly different product quality perception.*

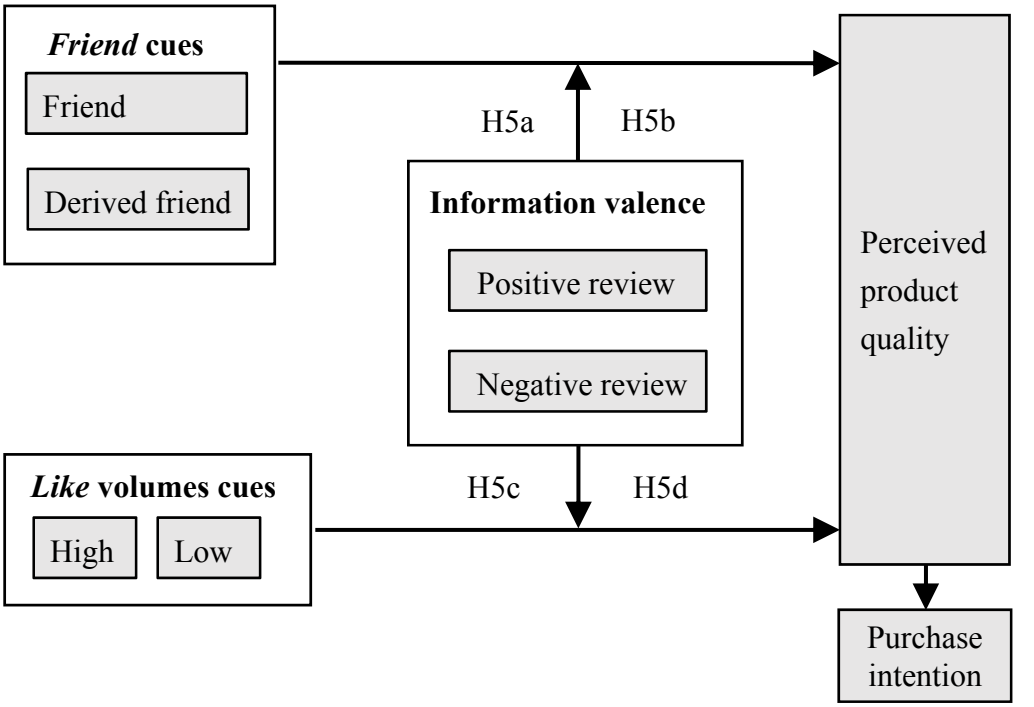


Figure 3. Research framework: Study 2

Data source: this research

2.7 Perceived Product Quality

Much research has focused on the relevance of consumers' ideas about product quality to buying behavior, and the strong relationship between perceived product quality and purchasing intent has been the subject of extensive literature over the past three decades (Dodds et al., 1991; Boulding & Kirmani, 1993; Rao et al., 1999; Sullivan & Kim, 2018). Wells et al. (2011) suggested that signals influence users' purchase intentions through perceived product quality. This study leverages new

avenues of research from the widespread adoption of social media to explore such relationships. Thus, we propose the following hypothesis:

Hypothesis 6*: The greater the perceived quality of a product, the more likely it is that a consumer will intend to buy it.*

3. Methodology and Results

Two studies to test our hypotheses were carried out in the form of experiments and are summarized in Table 1. Study 1 examined whether *friend* cues and *like* volumes can act as signals of product quality, focusing on the degree to which perceived product risk and perceived product familiarity moderate their effect. Study 2 emphasized the effect of information valence as *friend* cues and *like* volumes were manipulated as signals of product quality.

3.1 Experimental Platform

We conducted our experiment using Facebook as an SNS. We developed and launched a Facebook application that simulated participants' actual social networks. Facebook application technology offers several advantages. First, users could take part in our experiment by experiencing interaction within a realistic online environment, re-creating Facebook's. Consequently, we could incorporate real information regarding user interaction quickly and effortlessly because we could access the actual reactions of participants and their opinions expressed on Facebook. Additionally, carrying it out on Facebook allowed us to recruit a large number of participants within a short time frame.

Table 1. A Summary of the Experimental Studies

		Study 1	Study 2
Design		2×2 field experiment (Control group: Advertising information)	2×2×2 field experiment
Hypotheses tested		H1a, H1b, H2, H3a, H3b, H4a, H4b, H6	H5a, H5b, H5c, H5d, H6
Analysis method		ANOVA/Regression	ANOVA/Regression
Variables manipulated		● *Friend* cues ● *Like* volumes	● *Friend* cues ● *Like* volumes ● Information valence
Variables measured	Moderators	● Perceived product risks ● Perceived product familiarity	N/A
	Mediators	● Perceived product quality	
	Dependent variables	● Purchase intentions	

Data source: this research

3.2 Research Measures

We adapted all our research measures from earlier studies. However, questionnaire items from the existing literature were modified to fit the purposes of our study. A seven-point Likert scale was used to measure all the variables.

3.2.1 Perceived product quality. The measures of perceived product quality come from the studies of Jiang & Benbasat (2007) and Kempf & Smith (1998). The questions were mainly aimed at determining participants' satisfaction with the product.

3.2.2 Perceived product risk. Measures of perceived risk were developed for this study. The items sought to determine whether the purchase of the relevant product would be risky. Single-item measures were used in this study. Evidence suggests that simple measures with single items are as useful as multi-item measures for assessing perceived product risk (Ganzach et al., 2008).

3.2.3 Perceived product familiarity. This study used scales for perceived product familiarity from Lichtenstein & Fishhoff's (1977) research. Specifically, we assessed participants' product familiarity with three items that together represented an index. In short, the items aimed to determine how much the participants knew about a particular product.

3.2.4 Purchase intentions. According to Coyle & Thorson (2001), we measured intention to purchase using items that mainly assessed such variables as the participants' willingness, likelihood, and interest in the purchase of the product.

3.3 Study 1

This experiment took the form of a 2 × 2 between-subjects design, with one friend factor, friends and derived friends, and another *like* volume factor, high and low volumes. Together with a control group (given advertising information), this produced a total of 6 treatments. The design is presented in Table 2. With *friend* cues and *like* volumes as independent variables, the experiment measured their effectiveness as signals of product quality. Perceived product risk and perceived product familiarity were also measured for these six signal treatments to test H1a, H1b, H2, H3a, H3b, H4a, H4b, and H6. Four constructs were measured: product risk, product familiarity, product quality (all as perceived), and intention to purchase (as reported). The *friend* cue and *like* volume independent variables were also measured to check the experimental manipulations registered with participants.

Table 2. Study 1: Treatments

		Like volumes	
		High	Low
Friend cues	Friends	Treatment 1	Treatment 2
	Derived friends	Treatment 3	Treatment 4
Control group	Advertising	Treatment 5	Treatment 6

Data source: this research

3.3.1 Friend cues and like volumes. A *friend* cue refers to a recommendation concerning a product coming from two different possible sources, either a friend or a derived friend. In the friend treatments, the source of the recommendation was

ascribed to a friend of the participant on Facebook. In the derived friend treatments, the recommendation was sourced to one of the friends of the participant's friends on Facebook. Further, sourcing friends was achieved by randomly selecting participants from the Facebook friend lists. Sourcing derived friends involved randomly selecting from a list of a participant's friends' friends, that is, people who are friends of the participant's friends on Facebook. In the control treatment, advertising information provided recommendations. Participants saw advertising on their Facebook wall posts, which were named suggested posts. The suggested posts on a user's Facebook newsfeed were in an advertising format to allow advertisers to reach audiences.

The *like* volume independent variable had two different values of high and low volumes. Facebook's popular thumbs-up icon (*like* button) feature lets users rate and give their seal of approval to any post, link, or comment that they see. In particular, it allows them to give feedback as customers to others' posts about a product. We examined typical volumes and surveyed users to choose high and low values. Specific posts were randomly selected, and the number of *likes* had been checked. We selected messages from average users and excluded news, advertising, and fan-page messages, as these often get very many *likes*. Our observations showed that from zero to 15 was a typical range of *likes* for such messages. Accordingly, we decided 10 to 15 *likes* was a high *like* volume, and 0 to 5 *likes* was a low *like* volume. Additionally, non-participants in the experiment were surveyed for their opinions about these values and what they were used to seeing on Facebook. All of them agreed that on average, 10 to 15 *likes* was many *likes*, and 0 to 5 *likes* was only a few. Based on these observations and the survey, we can see that 15 was a good lower limit for high volumes and zero was good for low volumes. Accordingly, high *like* volume messages with product information had at least 15 *likes* and low volume messages had none.

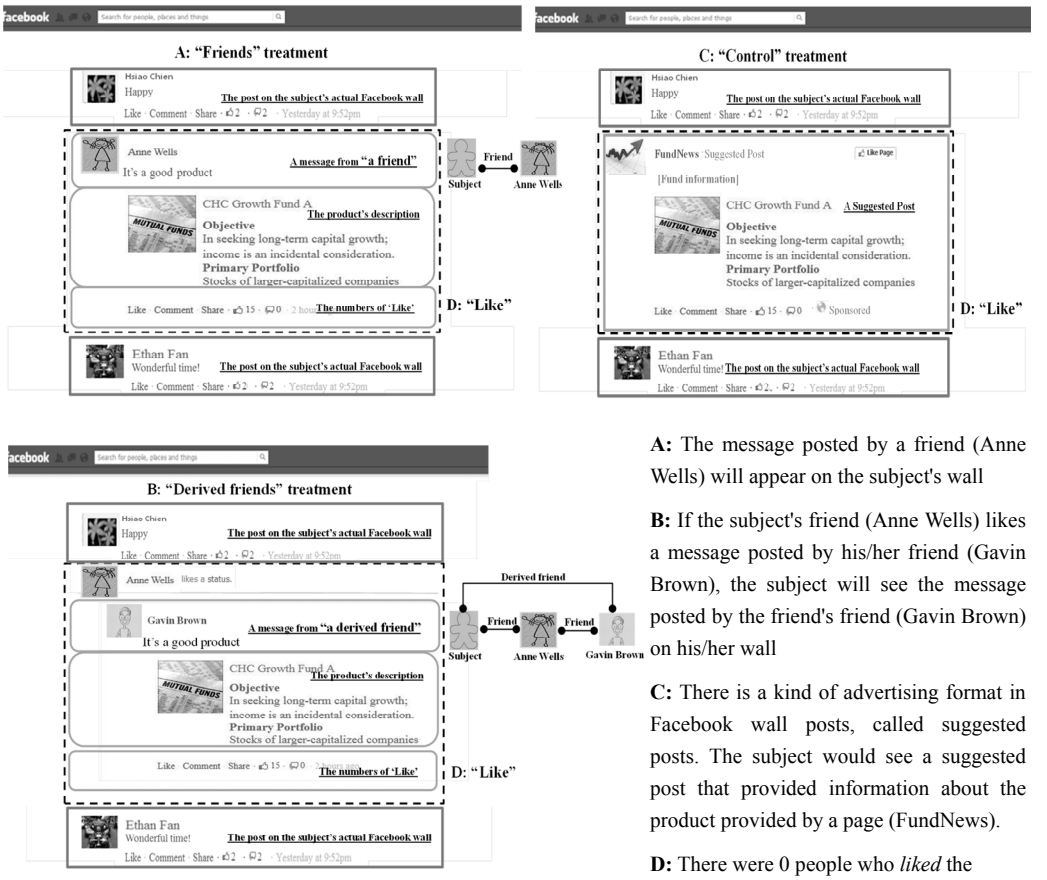
3.3.2 Moderating effects. Perceived product risk and perceived product familiarity were measured to test their moderating effects on perceived product quality. Each participant's average scores for these variables were first calculated, and the scores were coded as dummy variables to form additional indices. Finally, participants were classified using the median-split procedure (Aiken & West, 1991) to dichotomize the moderator variable. Scores above the median were assigned a

value of 1 and those below were coded as 0. The median perceived product risk was 4, which was the midpoint of the Likert scale used. Thus, average perceived product risk scores from 5 to 7 were assigned a value of 1, representing a high product risk level, and average perceived product risk scores up to 4 were given a value of 0, representing a low product risk level. The same rules were followed in the case of product familiarity, with a median of four.

3.3.3 Products described in experiment. The four products selected for this study were investment funds, smartphone apps, cars, and clothes. These products were selected because most people are potential consumers of them. More importantly, we sought to sample a wide range of goods at different prices to achieve more stable and generalizable results. Another concern was the research that found that consumers' familiarity with brands would change the degree to which advertising affects them (Kent & Allen, 1994; Campbell & Keller, 2003). We wanted to avoid the possibility that brand names would influence product quality inferences, so we created our own brand names and attached them to our four products. Each post presented to participants recommending a product containing a personal message from someone, all of which were positive, a photograph representing the product, and a description of the product.

3.3.4 Experimental design. The participants in each treatment group were called on to enter a virtual shopping environment and contemplate putting money into an investment fund, downloading a phone app, acquiring a car, or buying a t-shirt. While thinking about these purchases, they would notice that a virtual Facebook wall post constructed for them contained information about them (Figure 2). Wall posts were developed using two different sources of information. First, the last 10 posts on the real Facebook wall of participants the day prior to their participation in the experiment were reproduced. Second, 1 message recommending a product constructed by us was included, (saying, e.g., "It's a good product."). The content of the same nature was provided to the participants throughout the different treatment groups. The only way they differed was that different individuals provided the recommendations and varying numbers of *likes* were added to each post. In the "friends and high-volume" group, participants saw that 15 people had 'liked' it and that their friends had posted it. In the "friends and low-volume" group, participants

saw no one had ‘liked’ it and friends had posted it. In the “derived friends and high-volume” group, participants saw that 15 people had ‘liked’ it and derived friends had posted it. In the “derived friends and low-volume” group, participants saw no one had ‘liked’ it and derived friends had posted it. The control group received no such messages. Instead, they could read a suggested post that told them enough about the product to decide whether to buy it or not.



A: The message posted by a friend (Anne Wells) will appear on the subject's wall

B: If the subject's friend (Anne Wells) likes a message posted by his/her friend (Gavin Brown), the subject will see the message posted by the friend's friend (Gavin Brown) on his/her wall

C: There is a kind of advertising format in Facebook wall posts, called suggested posts. The subject would see a suggested post that provided information about the product provided by a page (FundNews).

D: There were 0 people who *liked* the message and thus were categorized as low-volumes. Conversely, when at least 15 people *like* the message, it is classified as high-volumes.

Figure 4. An Example: The Facebook Wall Posts Customized

Data source: this research

3.3.5 Pilot test. 20 people were enlisted to participate in a preliminary dry-run study to check for the presence of effects that would prevent the experiment from being a true test of the hypotheses and for other unforeseen aspects of our design that could interfere with the running of the real experiment. These people were shown the application in development, took part in the simulation, and answered a questionnaire afterward. What they had to say after they finished indicated that there were no major problems with the way the experiment was conducted. All treatment groups mostly agreed that the experience mirrored those they had while shopping online. After we explained the rationale of the study, they generally said that they thought that what they had seen and what they had done was in accordance with that rationale. They mostly just wanted to suggest changes to the way questions were phrased and to the design of the Facebook application.

3.3.6 Participants and procedures. We employed a market research company to send emails to Facebook users who might be interested in participating in the experiment. We recruited 581 participants: 360 (62%) women and 221 (38%) men. Most (64%) were 25–45 years old, had been on Facebook for 2 years or more (89.7%), and looked at their Facebook wall posts every day, or even more frequently (73.7%).

Randomization was used to place the participants in the groups. After the participants had agreed to take part, we told them how the virtual shopping experience would proceed. Next, we asked the participants to provide personal facts about themselves and explain the scenario and their role in it. Then, they presented the wall post we had constructed for them. Subsequently, the participants filled out a questionnaire.

3.3.7 Manipulation checks. To check the degree to which our *friend* cue differences were registered with the participants, two questions were presented and responses were recorded on a 7-point scale (1 = not at all, 7 = very well). The questions were "Do you know the recommender?" and "Are you well acquainted with the recommender?". The Cronbach's alpha value for these two items of 0.963 showed that *friend* cues were a single and reliable factor. In addition, there was a significant difference between scores for friends and derived friends ($M_{\text{derived friends}}$ = 2.02, M_{friends} = 6.55, $p < 0.001$). To validate *like* volume manipulation, we asked

participants to try to remember how many *likes* their message had received. Specifically, they read the statement: "More than 10 people clicked the *like* button for the product information provided by the recommender" and recorded the degree to which they disagreed or agreed on a 7-point scale (1 = absolutely false, 7 = true). The participants answered in a manner similar to the assumptions of our operational definitions. The difference between the responses of those whose messages had had no *likes* and those who had had 15 was significant ($M_{low\text{-}volume} = 2.66$, $M_{high\text{-}volume} = 6.17$, $p < 0.001$). Thus, it can be concluded the *friend* cue factor and the *like* volume factor were both successful manipulators.

3.3.8 Validity. A factor analysis with varimax rotation was performed on the six-item, two-construct data. The Kaiser-Meyer-Olkin (KMO) test, conducted to decide whether factor analysis was appropriate, returned a value of 0.863, greater than 0.5, which is usually thought to be sufficient (Hinton et al., 2014). The loadings of each item of the questionnaire were all above 0.8, indicating the validity of the constructs (Hair et al., 2018). The Cronbach's alpha coefficient values for the purchase intention and perceived product quality items were 0.958 and 0.933 respectively, higher than a value of between 0.70 and 0.90 we adopted (Nunnally & Bernstein, 1994) as our criterion of internal consistency and showing that the questions were each associated with the corresponding construct.

3.3.9 Hypothesis testing. A univariate analysis of variance (ANOVA) test was performed to analyze the main and interaction effects on the perceived product quality of the experimental and control conditions, with the results shown in Table 3.

The analysis indicated *friend* cues had a significant primary effect ($F = 40.244$, $p < 0.001$), with the 'friends' group deciding the product had significantly higher quality than the "derived friends" group ($M_{friends} = 4.98$ vs. $M_{derived\ friends} = 4.23$, $p < 0.001$), who in turn thought it had higher quality than the control group ($M_{derived\ friends} = 4.23$ vs. $M_{control\ group} = 3.51$, $p < 0.001$). There was also a significant primary *like* volume effect ($F = 19.528$, $p < 0.001$). A t-test comparing perceived product quality elicited by either low or high *likes* showed significantly higher product quality, ascribed in the latter case ($M_{low\text{-}volume} = 3.95$, $M_{high\text{-}volume} = 4.56$, $p < 0.001$). Accordingly, Hypotheses 1a, 1b, and 2 were accepted.

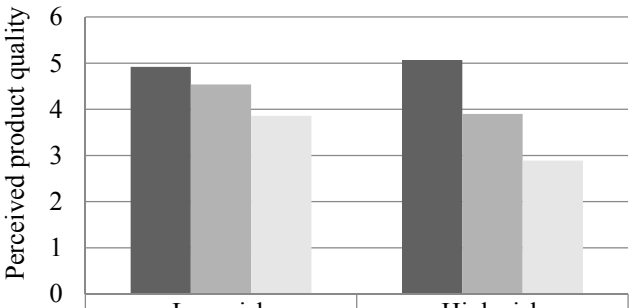
Table 3. Study 1: ANOVA Results

Effect	Sum of squares	F	Sig.
Friend cues	80.523	40.244	.000
Like volumes	39.074	19.528	.000
Product risk	13.148	6.571	.011
Product familiarity	43.210	21.596	.000
Friend cues × *Like* volumes	.208	.104	.901
Friend cues × Product risk	6.036	3.017	.050
Friend cues × Product familiarity	7.796	3.896	.021
Like volumes × Product risk	5.037	2.517	.113
Like volumes × Product familiarity	.332	.166	.684
Product risk × Product familiarity	.006	.003	.957
Friend cues × *Like* volumes × Product risk	.642	.321	.726
Friend cues × *Like* volumes × Product familiarity	3.164	1.581	.207
Friend cues × Product risk × Product familiarity	2.789	1.394	.249
Like volumes × Product risk × Product familiarity	1.934	.967	.326
Friend cues × *Like* volumes × Product risk × Product familiarity	.899	.449	.638

Data source: this research

As for interactions between the *friend* and *likes* factors and perceptions about the products, *friend* cues interacted significantly with perceived product risk ($F = 3.017$, $p < 0.1$). When a product's risk was high, exactly as with the primary effect of 'friends,' recommendation by a "friend" resulted in higher perceived product quality than a recommendation from a "derived friend" ($M_{friends} = 5.07$ vs. $M_{derived\ friends} = 3.90$, $p < 0.001$), which in turn resulted in higher product quality perceptions than from an advertisement in the control group ($M_{derived\ friends} = 3.90$ vs. $M_{control\ group} = 2.89$, $p < 0.001$). However, when purchasing a product was not seen to be risky, friends' recommendations produced almost the same perceptions of product quality as derived friends' recommendations ($M_{friends} = 4.92$ vs. $M_{derived\ friends} = 4.54$, $p = 0.165$); at the same time, a product recommended by a friend ($M_{friends} = 4.92$, $p < 0.001$) or a derived friend ($M_{derived\ friends} = 4.54$, $p < 0.001$) each led to higher perceived product quality than did the control condition ($M_{control\ group} = 3.86$). The results are shown in Figure 3. Thus, we accept Hypothesis 3a. The corresponding interaction effect between *like* volumes and product risk, as perceived, was not significant ($F = 2.517$,

p = 0.113). In other words, *like* volume effects on product quality perception were significant in both the high- and the low-risk condition, but the impact of *like* volumes on perceived product quality did not differ with the product risk level. As a result, we rejected Hypothesis 3b.



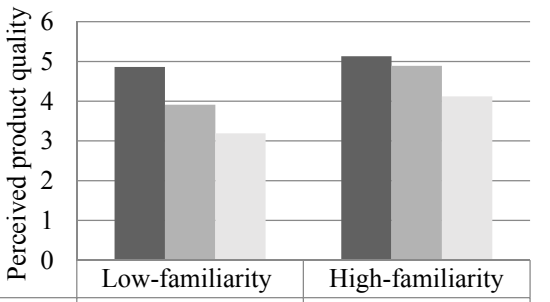
	Low-risk	High-risk
Friends	4.92	5.07
Derived friends	4.54	3.90
Control group	3.86	2.89

Figure 5. The Interaction between Friend Cues and Perceived Product Risk

Data source: this research

The interaction of *friend* cues with product familiarity perceptions was also significant ($F = 3.896$, $p < 0.05$; Figure 9). In cases of low product familiarity, as we saw with the primary effect of familiarity, a friend's recommendation elevated perceived product quality over that when the recommendation came from a derived friend ($M_{friends} = 4.86$ vs. $M_{derived\ friends} = 3.91$, $p < 0.001$), and the derived friend's recommendation produced a quality perception more favorable than that produced by advertising ($M_{derived\ friends} = 3.91$ vs. $M_{control\ group} = 3.19$, $p < 0.001$). However, when participants considered themselves to be familiar with the product, the effect of a friend and a derived friend's recommendation was not significantly different ($M_{friends} = 5.13$ vs. $M_{derived\ friends} = 4.89$, $p = 0.620$). However, if the product was recommended by a friend ($M_{friends} = 5.13$, $p < 0.001$) or a derived friend ($M_{derived\ friends} = 4.89$, $p < 0.05$), each had a higher perceived product quality than the control condition ($M_{control\ group} = 4.12$). The results are shown in Figure 4. Because of this difference in the cases of high and low familiarity, we accept Hypothesis 4a. However, the corresponding interaction effect for *like* volumes and product familiarity, as perceived, was not significant ($F = 0.166$, $p = 0.684$). In other words, *like* volumes

significantly affected quality perception both when participants knew little about the product and when they were familiar with it, and that impact of *like* volumes on quality perceptions did not vary with different product familiarity levels. Thus, we reject Hypothesis 4b:



	Low-familiarity	High-familiarity
Friends	4.86	5.13
Derived friends	3.91	4.89
Control group	3.19	4.12

Figure 6. The Interaction between Friend Cues and Perceived Product Familiarity

Data source: this research

Regression analyses were conducted to examine the effects of perceived product quality on purchase intentions. The results of these analyses are presented in Table 4 and show that the intention to purchase was positively and significantly affected by participants' perceptions of the product's quality ($b = 0.618$, $p < 0.001$). In addition, these product quality perceptions partially mediated the *friend* cue and *like* volume determination of intention to purchase, explaining 48% of the variance in the latter variable. Hence, H6 was accepted.

Table 4. Study 1: Regression and Mediation Analysis for Purchase Intentions

	Variables	Standardized coefficient	Sig.
IV on DV	*Friend* cues, purchase intentions	.361	.000
	Like volumes, purchase intentions	.194	.000
IV on Mediator	*Friend* cues, perceived product quality	.371	.000
	Like volumes, perceived product quality	.192	.000
IV on DV with Proposed Mediator	*Friend* cues, mediator, and purchase intentions	.132	.000
	Like volumes, mediator, and purchase intentions	.075	.014
	Perceived product quality, purchase intentions	.618	.000

Data source: this research

3.4 Study 2

A second experiment with the same two-level *friend* cues and *like* volumes, plus the additional independent variable of information valence (positive versus negative messages), was carried out to check the impact of information valence on the signaling provided by the first 2 independent variables, testing H5a, H5b, H5c, H5d, and H6. The experiment is presented in Table 5. The measured constructs included the dependent variables, product quality (as perceived), and intention to purchase (as reported). *Friend* cues, *like* volumes, and information valence (as reported) were also measured for manipulation check purposes.

Friend cues and like volumes were operationalized, using the same treatments Study 1 introduced. Positive and negative information valences were operationalized using two versions of the recommendation messages. These messages were "It's a good product" and "It's NOT a good product" for positive and negative information, respectively. The other aspects of the experiment were the same as in the first study, including the four investment funds, cars, apps, and clothes products, the experiment's design, the recruitment of participants, their experience of the Facebook application, and the handling of the data.

Table 5. Study 2: Treatments

Treatment	*Friend* cues	*Like* volumes	Information valence
1	Friends	High	Positive
2	Friends	High	Negative
3	Friends	Low	Positive
4	Friends	Low	Negative
5	Derived friends	High	Positive
6	Derived friends	High	Negative
7	Derived friends	Low	Positive
8	Derived friends	Low	Negative

Data source: this research

3.4.1 Participants. We conducted a field experiment in which users were invited to take part in the Facebook application used in this series of experiments. In total, 798 subjects were recruited; 465 (58.3%) were women and 333 (41.7%) were men. Most (65.6%) were 25–45 years old, had been on Facebook for 2 years or more (86.1%), and looked at their Facebook wall posts every day, or even more frequently (71.8%).

3.4.2 Manipulation checks. *Friend* cues and *like* volumes manipulation checks were conducted using the same procedures detailed in Study 1. *Friend* cues ($M_{\text{derived friends}} = 1.88$, $M_{\text{friends}} = 6.46$, $p < 0.001$) and *like* volumes ($M_{\text{low-volume}} = 2.77$, $M_{\text{high-volume}} = 5.67$, $p < 0.001$) were significant. To check information valence, we asked the following question: "The message about the product review is positive" and recorded responses on a 7-point scale (1 = absolutely false, 7 = absolutely true). The participants' answers agreed with the operational definitions. The difference between the reports of those receiving positive messages and those receiving negative messages was significant ($M_{\text{positive}} = 6.05$, $M_{\text{negative}} = 1.89$, $p < 0.001$). Therefore, we conclude that all the variables were successfully manipulated.

3.4.3 Validity of measurement instrument. The procedure by which the validity and reliability of the construct was assessed was the same as that in Study 1. A factor analysis with varimax rotation was carried out on the 6-item, 2-construct data provided by the participants' responses. The Kaiser-Meyer-Olkin (KMO) test, conducted to decide whether factor analysis was appropriate, returned a value of 0.867, greater than 0.5, which is usually thought to be sufficient (Hinton et al., 2014). The loadings of items of the questionnaire were all above 0.8, indicating the validity of the constructs (Hair et al., 2018). The Cronbach's alpha coefficient values for the purchase intention and perceived product quality items were 0.949 and 0.933 respectively, higher than a value of between 0.70 and 0.90 we adopted as our criterion of internal consistency, and showing that the questions were each associated with the corresponding construct (Nunnally & Bernstein, 1994).

3.4.4 Testing hypothesis. A univariate analysis of variance (ANOVA) test was again performed to analyze the interaction effects on perceived product quality of the experimental and control conditions, with results shown in Table 6 and Figure 5.

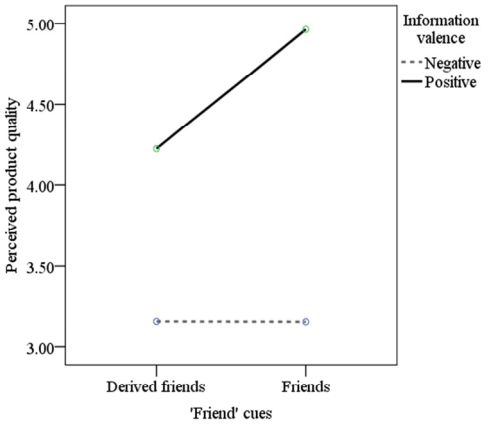
The *friend* cues × information valence interaction results ($F = 12.411$, $p < 0.001$) reveal that *friend* cues have a stronger impact on perceived product quality under positive-recommendation conditions than under negative-recommendation conditions. When the recommendation was positive, the level of perceived product quality was greater when the product was recommended by a friend than when the product was recommended by a derived friend ($M_{friends} = 4.98$ vs. $M_{derived\ friends} = 4.23$, $p < 0.001$). In contrast, in cases where the recommendation was negative, there was no significant difference between the effect of the friends and derived friends' recommendations ($M_{friends} = 3.15$ vs. $M_{derive\ friends} = 3.16$, $p = 0.971$). Thus, H5a and H5b were both accepted. There was also a significant *like* volumes × information valence interaction ($F = 8.106$, $p < 0.01$). The number of *likes* had a stronger impact on perceived product quality under positive-recommendation conditions than under negative-recommendation conditions. When the recommendation was positive, a product recommended with high *like* volumes was perceived as having better quality than one recommended with low *like* volumes ($M_{high\text{-}volume} = 4.89$ vs. $M_{low\text{-}volume} = 4.32$, $p < 0.001$). In contrast, in cases where the recommendation was negative, the differences produced by high-volume *likes* and low-volume *likes* were not significant ($M_{high\text{-}volume} = 3.13$ vs. $M_{low\text{-}volume} = 3.18$, $p = 0.746$). Thus, H5c and H5d are also accepted.

Table 6. Study 2: ANOVA Results

Effect	Sum of squares	F	Sig.
Friend cues	26.959	12.251	.000
Like volumes	12.802	5.818	.016
Information valence	411.763	187.126	.000
Friend cues * *Like* volumes	1.794	.815	.367
Friend cues * Information valence	27.309	12.411	.000
Like volumes * Information valence	17.836	8.106	.005
Friend cues * *Like* volumes * Information valence	.926	.421	.517

Data source: this research

Friend cues and information valence



Like volumes and information valence

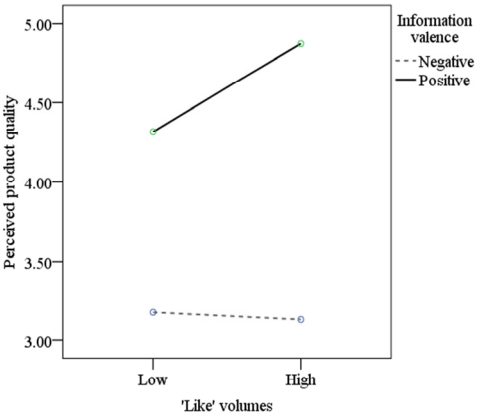


Figure 7. Two-Way Interactions for Perceived Product Quality

Data source: this research

Regression analyses were conducted to examine the effects of perceived product quality on purchase intentions. The analysis results are presented in Table 7 and show that the intention to purchase was significantly affected in a positive direction by participants' perceptions of the product's quality ($b = 0.663$, $p < 0.001$). In addition, these product quality perceptions partially mediated the *friend* cue and *like* volume determination of intention to purchase, explaining 48.1% of the variance in purchase intentions. Hence, H6 was supported.

Table 7. Study 2: Regression and Mediation Analysis for Purchase Intentions

	Variables	Standardized coefficient	Sig.
IV on DV	*Friend* cues, purchase intentions	.198	.000
	Like volumes, purchase intentions	.116	.001
IV on Mediator	*Friend* cues, perceived product quality	.119	.001
	Like volumes, perceived product quality	.089	.012
IV on DV with Proposed Mediator	*Friend* cues, mediator, and purchase intentions	.119	.000
	Like volumes, mediator, and purchase intentions	.057	.027
	Perceived product quality, purchase intentions	.663	.000

Data source: this research

4. Discussion and Conclusion

This study applies the signal theory framework to develop a holistic understanding of how online recommendations with different social signals (in our case, *friend* cues and the presence of *likes*) affect online consumer behavior. The role of the emotional system in decision-making is fundamental, and social interactions often influence the way this system works. Therefore, we can change consumer behavior by cueing specific signals in socially interactive environments. An increase in information transmitted via SNSs accompanies an increased vitality in determining consumer opinions. Social network cues have the potential to influence consumers powerfully.

This study expands the theoretical reach of the signaling theory to include sharing consumer information on SNSs. In so doing, this study enhances understanding of how theories from other fields (in this case, signaling theory) can inform economic theory and explain user behavior in the context of imperfect-information social commerce purchase decisions. This study performed two experiments with *friend* cues and *like* volume social signals on Facebook. Our experiments determined that these two social signals might be viable effectors of better product quality perceptions and purchase intentions. Furthermore, we identified two essential facilitators heightening the effects of social signals: (1) high product risk and (2) low product familiarity.

Additionally, other studies have investigated the role of social signals in consumers' decision-making (Utz et al., 2012); however, such studies have been limited to the impact of online consumer reviews in the area of electronic commerce. Our study extends this knowledge by determining the effects of social cues on SNSs through experimental manipulation. Furthermore, the existing research focuses mainly on how positive reviews affect consumer decisions, which is somewhat limited because consumer reviews may be either negative or positive. We examine social signals in the context of both negative and positive reviews and find that when the review is positive, social signals have a more significant impact than when the reviews are negative. Therefore, we contribute significantly to the existing research.

4.1 Theoretical Contributions

Our findings have broad implications in several areas. First, we found the connection between *friend* cues and product quality judgments is important. Consumers tend to believe that a product is better if the information used to reach that conclusion comes from someone they know well. This finding supports earlier studies, which found that friends' recommendations are more credible than recommendations from other people; the closer the friend, the more influential their recommendations are (Brown & Reingen, 1987; Rogers, 2003; Adams, 2011).

Second, this study shows that trust is transitive; in other words, the information provided by derived friends leads to higher perceived product quality than that provided by advertising ($M_{friends} = 4.98 > M_{derived\ friends} = 4.23 > M_{control\ group} = 3.51$). This reinforces Shih's assertion that trust can spread to friends who are two steps away because social network maps allow mutual friend discoveries and facilitate trust transfer (Shih, 2010).

Third, we confirmed that product quality judgments are influenced by the number of times other SNS users clicked *like* on messages about that product. A large number of *likes* drives positive purchase decisions more than fewer *likes*. Our finding is also in line with Muchnik et al. (2013), who found that a user's *like* in a site comment will likely prompt a friend to approve the comment. The domination of SNSs in the present era has made the volumes of terms like *comment*, *follower*, *like*, *share*, *tweet*, and *Google +1* increasingly important for online user behavior and consumer purchase behavior.

Fourth, we examined the effects of the negative reviews. As expected, positive and negative information affects consumer behavior differently. We found that positive and negative reviews do not have an equivalent impact on consumers' perceived product quality. Whether the social signal comes from a friend or the friend of a friend, consumers use information valence by privileging negative reviews even if more people like the product. When presented with positive messages, consumers are more likely to look carefully at all available information. Therefore, social signals (*friend* cues and *like* volumes) may cause a user to feel more confident in having a positive opinion about products. However, according to the category diagnosticity theory, consumers will feel less need to attend to such social signals

when presented with negative messages since negative information is considered more useful and diagnostic (Ahluwalia, 2002). By presenting messages with different information valences in combination with different signals, this study demonstrates that information valence (positive vs. negative information) moderates the influence social signals have on consumer quality judgments. Since negative information already impacts perceived product quality more strongly than positive information, people may not appreciate added information from social signals in reaching quality decision conclusions. However, given positive information, social signals could further enhance product quality judgments and subsequent purchase decisions.

Finally, perceived product risk, a contingent effect of our experimental intervention, influenced the degree to which *friend* cues informed product quality judgments. When making decisions about products with different degrees of risk, consumers' thought processes may not be the same (Zhang & Li, 2006; Lian & Lin, 2008). When consumers think that purchasing a product is risky, they will be inclined to scrutinize their information and the degree to which the information sources can be trusted. Therefore, friends' recommendations create a higher perceived product quality than derived friends' recommendations, creating a higher perceived quality than recommendations under the advertising control condition. When a purchase is not seen as risky, consumers are not as interested in scrutinizing information about the product and are less concerned about how much trust they place in their sources. Similar contingent effects occur in the context of perceived product familiarity. Product familiarity influences the degree to which *friend* cues inform product-quality judgments. Low product familiarity likely forces consumers to depend on signals more because they cannot use intrinsic product attributes to make judgments (Rao & Monroe, 1988).

However, there was no similar moderating effect of contingent product risk and product familiarity judgments on *like* volumes. Interestingly, no boundary conditions were observed. Regardless of product risk and familiarity judgments, the number of *likes* exerted an equally useful degree of influence. Moreover, this effect is significant. One possible explanation is how easily information can be incorporated into product understanding. A large number of *likes* means that the product in the

message will stand out that people have already judged. Additionally, *like* volumes are signals that are easy for users to understand. When potential customers are presented with a message about a product with many *likes*, they immediately see many people recommend its purchase. For this reason, *like* volumes automatically and immediately register with consumers. Furthermore, users do not appraise *like* volumes differently, irrespective of the feelings of riskiness or unfamiliarity the product may elicit.

4.2 Managerial Contributions

This study has several practical implications. First, it adds quantitative reinforcement to Adams' (2011) assertion that the future of advertising uses multiple lightweight interactions. Furthermore, the results illustrate the continuing dominance of social networks on SNSs. Enabling social network signals has become increasingly important in marketing because social network signals influence both quality perception and purchase intention. Additionally, social network signaling is a highly efficient marketing tool; marketers may harness the power of signaling by putting *like* or *share* links on their product websites so that motivated users can share information about appealing products with their friends. Enabling consumers to share positive reviews can lead to an explosion of approvals (Muchnik et al., 2013).

Second, both friends and derived friends had a more significant influence than advertising. Previous studies have estimated that a Facebook user with 130 friends may have approximately 10,000 derived friends (Adams, 2011). Therefore, companies that actively invite consumers to recommend their products on social networks may experience significant multiplier effects.

Third, this study also provides insight into circumstances where social networks have the most powerful impact on consumer purchase decisions. It is likely more advantageous for companies to communicate with consumers through friends when they do not know much about the product or think its purchase is risky. In these circumstances of high risk and low familiarity, marketers should have potential peers of the targeted individuals communicate their support for the product. Friends influence friends. In other words, friends like what their friends like; it is critical to promote the idea that friends like a product if consumers are unfamiliar with it or

think purchasing the product is risky. In this way, companies can help consumers evaluate products while simultaneously creating greater interest among potential users.

Finally, managing negative information is important because the influence exerted by a negative message can be more substantial than a positive one (Basuroy et al., 2003; Chevalier & Mayzlin, 2006). Marketers should examine negative comments more closely than positive comments and use negative comments as a chance to respond, learn, and improve future products. Relatively few negative comments can ruin the social signals of *likes* accumulated by users in their networks. Therefore, digital marketing practitioners could invest more technology and time in detecting and monitoring negative comments on social media platforms rather than being complacent with positive feedback.

4.3 Limitations and Future Research

While this study's signaling framework should be retained, it could be extended to cover the effect of signals on consumer cognition as other factors are introduced. Established effectors of behavioral intentions (e.g., emotional states, needs, and personality characteristics, such as skepticism) could also be folded into the signaling framework. Social signals probably interact with these variables and may have differing effects on quality judgments and purchase intentions. These are other parameters of the buying behavior process, outside the friend, derived friend, and *like* social signals that we studied, whose impact future studies of SNS social signaling may decide to research.

Additionally, consumer behavior follows patterns determined by buying histories, likes and dislikes, and the reliability of the information, which this study did not examine. Such determiners should be examined in future studies to gain increased insight. We also need to note that this study only established the general effects of a population of Facebook users, and individual responses to signals vary from one user to another. Further work may be critical in understanding how factors, such as the number of friends a user has and their degree of SNS activity, affect social signals' potential effects.

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