LIKE VERSUS DISLIKE: HOW FACEBOOK’S LIKE-BUTTON INFLUENCES PEOPLE’S PERCEPTION OF PRODUCT AND SERVICE QUALITY

Completed Research Paper

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Abstract

As Facebook’s Like-button has become ubiquitous, it is the purpose of this research to investigate (1) whether Likes serve as a signal of a product’s or service’s quality and (2) how the introduction of a Dislike-button would alter perceptions. Following a qualitative study, we conducted an experiment in which 653 participants were presented with website screenshots featuring varying levels of Likes and Dislikes. The results indicate that the theoretical framing of Likes as a Signal is valid and that people do perceive the quality of products and services as superior when they are associated with more Likes. Signaling also explains the counter-intuitive finding that Dislikes can have a positive effect on people’s quality perceptions. Results are discussed with respect to theory and practical implications.

Keywords: eCommerce, Consumer Behavior, Perceived Quality, Signaling, Facebook
Introduction

As consumers form their impression regarding products and services online, they have access to a multitude of information sources such as expert reviews, customer evaluations, blogs and advertisements. The availability of these information sources on the Internet shows the immense economic impact of IT on today’s commerce beyond just eCommerce, underlying IT’s new strategic role.

Nobel laureate economist Herbert A. Simon (1995, p.200) famously noted: “...a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it.” Recently, a standardized feedback metric has spread rapidly throughout the Internet: Everyday, Facebook’s Like-button is clicked by millions of people worldwide. As tiny as it may seem, the simplistic concept of the Like-button is a significant innovation as it provides consumers with a comprehensible feedback signal on a global scale.

Whether it is a small merchant or a multinational brand, all it takes is to “copy-and-paste” a few lines of code to include the Like-button. Adoption is rapid: within its first year, the feature has been implemented by more than 2.5 million websites, among them 80% of the top frequented websites of the United States and every day more than 10,000 websites add the feature (Parr 2011).

Little is known about the perception of Likes. What does it mean for brands to include Facebook’s Like-feature on their website? Do Likes influence the perception of consumers? Can Likes drive sales? While numerous studies have shown that customer reviews can have a positive effect on sales (Chen et al. 2008; Chevalier and Mayzlin 2006; Clemons et al. 2006; Ghoose and Ipeirotis 2006) it is unclear how the simplistic concept of a Like-button influences the impression formation process of consumers.

Online customer reviews can be defined as “peer-generated product evaluations posted on company or third party websites” (Mudambi and Schuff 2010, p.185). Chen et al. (2008) found that the helpfulness of a review drives sales. The helpfulness of a review is positively influenced by its depth (Mudambi and Schuff 2010). Meanwhile, a Like is perhaps the least deep form of a customer review: it is a one-sided signal allowing only for positive evaluations.

Likes provide consumers with an absolute number – without any reference which would allow them to put this number in relation. People can only guess from its total amount how many people may have implicitly ‘disliked’ by refraining from ‘liking’. Given the rapid diffusion of the Like-button, it is the purpose of this study to shed light on people’s perception of this feature. Specifically, we investigate whether Likes serve as a signal of a product’s or service’s quality which is a predictor of purchase intention (Wells et al. 2011): Further, it is our aim to explore how the introduction of a Dislike-button would alter perceptions. It may be straightforward to expect Dislikes to negatively influence people’s quality expectations. However, coming from a status quo in which the Like-button has been established as a one-sided signal, solely allowing for Dislikes may serve as a signal in itself. We think this subject deserves attention, as the literature on two-sided signals does not inform us on how this historic aspect may play out.

This leads us to the following research question: How do Likes and (hypothetically) Dislikes influence people’s perception of product quality?

Our findings apply to Facebook’s Like-feature as it appears outside the platform. Of course, pages and posts on the Facebook platform itself can be ‘liked’ as well. Certainly, brands as well as consumers do not necessarily regard Likes as an evaluation tool as it may serve a number of other functions, particularly sharing content with friends. Even more so, it is important to understand how Likes can actually trigger purchase decisions by subconsciously improving people’s quality expectations.

To this end, we proceed as follows: We theoretically frame Likes as a potential signal of product quality. Then we report on an experimental study investigating whether people’s perception regarding the quality of a product or service is influenced by the number of Likes and Dislikes it is associated with. We conclude by discussing the results with respect to both theory and practical implications.
Theoretical Foundation and Model

As consumers often must make purchase decisions with incomplete information about a product’s quality, they make inferences about the quality based on cues that are extrinsic to the product (Biswas and Biswas 2004; Zeithaml 1988). For example, a warranty (Yen 2006) or the quality of the website that sells the product (Kim et al. 2004; Wells et al. 2011) does not change intrinsic attributes of the product but may create trust which reduces uncertainty in the purchase decision process. These are signals consumers rely upon, as acquiring knowledge about a product is costly and time consuming.

Consequently, a signal can be defined as a cue that a seller can use “to convey information credibly about unobservable product quality to the buyer” (Rao et al. 1999, p. 259). Signaling Games are based on a dynamic setting in which an agent possesses information which the principal does not have. The principal cannot know whether the information communicated by the agent is correct or false, preventing transactions to occur. Akerlof (1970) shows that, in the absence of signals, quality uncertainties may even prohibit market exchanges of high quality products (given there are only two types of products, i.e., high quality and low quality). In his seminal work, Spence (1973) presents a micro-economic model to show that transaction risks due to information asymmetry may be overcome by appropriate signals of the informed player.

Signaling Theory has been applied in a multitude of disciplines (e.g., Benartzi et al. 1997; Certo 2003; Kirmani 1997; Turban and Greening 1997). It allows us to understand how potential buyers and sellers behave under conditions of information asymmetry, specifically, in pre-contractual situations. Kirmani and Rao (2000) provide an overview of the literature on signaling unobservable product quality in order to understand how consumers assess product quality when faced with information asymmetries. They present ways business can signal product quality through advertising, brand building, pricing, warranties and other marketing-mix variables.

Wells et al. (2011) present an application of Signaling Theory in IS research as they investigate how the quality of a website influences people’s perception of product quality and purchase intention. They find that various qualities of a website do have a significant influence on how people perceive the quality of a featured product.

Basically, products can be classified with respect to the degree of pre- and post-purchase information scarcity. In the case of experience goods, it is particularly difficult for consumers to assess the quality of a product prior to purchase. Experience goods require sampling or purchase for evaluation. In the case of search goods, consumers can obtain information on the quality of a product or service prior to purchase (Nelson 1970; 1974).

When consumers browse the Internet they are not able to touch or smell a product, or talk to a salesperson face to face- all of which would provide important cues to consumers who are uncertain about the quality of a product. Signals may not only be sent from sellers to consumers, but also among consumers. The Internet allows for information exchange among consumers on a large scale, for example through online customer reviews (e.g., Mudambi and Schuff 2010). Signaling theory is concerned with understanding why certain signals are reliable and thus relevant for consumers’ purchase decision. This provides a suitable framework for studying the impact of people’s Likes and potentially Dislikes on other people’s perceptions of product quality.

**Likes as a signal of product quality**

There is numerous empirical evidence that people’s perceptions are subject to other people’s opinions. For example, consumers rely on other people’s suggestions with respect to restaurants (Zhang 2010) and movie screenings (Liu 2006). Bolton et al. (2004) show the impact of third-party signals on people’s willingness to perform a risky transaction. In his famous experiments, Asch (1951; 1955) even showed that participants changed their own opinion and adapted it to the majority opinion even when the majority was apparently wrong. A large number of people ‘liking’ a product may positively influence an individual’s perception regarding the quality of a product.

By adapting Signaling models to a context of user generated evaluations we will assume that costs rise with a product’s quality which implies an incentive for the agent to communicate high quality but provide...
likes can then only be a signal if the principal (i.e., the potential buyer) cannot observe the actual quality, which naturally is the case with experience goods.

The particular challenge of understanding Likes as a signal is that it is unclear whether Likes are actually a signal from sellers to consumers, or a signal sent from consumers to other consumers. After all, every business is free to include Facebook’s Like-button or not. Likes can only be a credible signal of product quality if agents who offer a lower quality product have higher costs acquiring Likes than those offering a high quality product.

Which products receive more Likes and which receive less? It may be assumed that people have a higher tendency to ‘like’ a product which they attribute a higher quality as opposed to those which they attribute a bad quality. This would mean that higher quality products would receive more Likes without any extra costs. Lower quality products would then have to acquire Likes in different ways. These ways may include usage (and prior acquisition of) fake Facebook accounts to ‘like’ the lower quality product, or the provision of an incentive for people to ‘like’ it – all of which creates costs. Therefore, as for those products which do feature a Like-button, consumers can expect that the number of Likes either stems from happy customers or investments into marketing efforts to artificially increase the number of Likes.

Uncertainty regarding the credibility, preferences and expertise of the reviewer (e.g., the people who ‘liked’) may offset the effect of Likes on people’s perception. However, micro-economic modeling of evaluation systems with binary signals shows that this concern does not necessarily affect the market outcome: in the case of uncertainty about the trustworthiness of the reviewers, principals (i.e., consumers) adapt their perception of the signal by adding a discount factor leading to the market outcome as in the case of certainty about reviewers’ characteristics (Dellarocas 2000).

Despite concerns regarding possible biases of reviews (McDonald and Slawson Jr. 2002) most studies show significant effects of online rating signals on people’s bidding behavior (Dewan and Hsu 2004, Houser and Wooders 2006; Lee et al. 2000) and product purchases (Chen et al. 2008; Chevalier and Mayzlin 2006; Clemons et al. 2006; Ghose and Ipeirotis 2006; Mudambi and Schuff 2010).

Given the costs involved in faking Likes in conjunction with the empirical evidence that individuals put trust in other people’s opinions and online reviews, we expect Likes to influence people’s expectations of product quality:

**H1**: Likes are a signal of product quality, in that the number of Likes associated with a product has a positive influence on people’s perception of product quality.

The hypothesized effect of Likes on people’s quality expectations is depicted on Figure 1.
**Dislikes and two-sided signals**

If Likes are a signal of product quality, does this mean that Dislikes constitute the exact same signal with the reverse effect? For example, do 100 Likes lead to the same perception as 110 Likes combined with 10 Dislikes do?

Humans rely on references in order to evaluate things (e.g., Ariely 2008). How many Likes are good? How many Likes are bad? Providing a diametrical metric, i.e., Dislikes allow people to interpret the signal in relative instead of absolute terms. This may make people more aware of the Likes. According to the blemishing-effect, additional negative cues trigger an intuitive reprocessing of positive baseline evaluations. As a result, the appeal of a product may be enhanced by making its positive attributes seem more positive (Ein-Gar et al. 2012).

Therefore, looking at Likes and Dislikes as opposite directions of a binary signal may not capture the realities of the human perception formation process. In fact, the literature on two-sided messages in advertising offers a multitude of examples how negative information can actually improve opinions about products (e.g., McGuire 1985; Pechmann 1992; Pechmann and Stewart 1990). However, the effect of two-sidedness in consumer-to-consumer communication is unclear. How negative information influences people’s perceptions is complex: a variety of variables moderate and mediate the effect. The persuasive impact depends on how much negative information is included, where it is placed, the correlation consumers expect between negative and positive attributes and the marketers’ voluntariness to communicate the negative information (see Eisend 2006 for a meta-analysis).

Signaling theory implies that all agents can send the same signal, regardless the quality they provide, but at different costs. Whether a cue, in fact, signals quality depends on the credibility. While the net-effect of negative information such as Dislikes is subject to a multitude of interacting factors, it is the bottom line that message sidedness has a positive effect on source credibility (e.g., Bohner et al. 2003; Hastak and Park 1990; Hunt et al. 1982; Kamins and Marks 1987; Pechmann 1992; Smith and Hunt 1978; Trifts and Häubl 2003). This shows that negative information does not necessarily reduce the influence of positive information on people’s perceptions. The negative information may be a signal for credibility. This is why we frame Dislikes as a separate signal rather than looking at it as a diametrical force to Likes.

Given the empirical evidence on the effect of negative information, a low number of Dislikes may improve credibility and, consequently improve people’s quality expectations for any given number of Likes:

**H2a:** Introducing a low number of Dislikes to a low number of Likes has a positive influence on people’s perception of product quality.

**H2b:** Introducing a low number of Dislikes to a high number of Likes has a positive influence on people’s perception of product quality.

Meanwhile, consumers will perhaps expect bad quality of a product if it is associated only with Dislikes and zero Likes. This speaks for an interaction effect in that additional negative information may increase the credibility but draw the signal direction downward, resulting in a negative net-effect on people’s quality expectations.

This can be accounted for by a structural model with two diametrical determinants of product quality perception: Source credibility and direction of the signal. Indeed, the net-effect of both factors has been investigated by Eisend (2006) who finds a curvilinear relationship between the amount of negative information in advertising and brand attitude, i.e., too much negative information is bad. In an IS context, similar interaction effects were found with respect to investments in website quality (Wells et al. 2011).

Therefore, we expect the quality of products associated with a high number of Dislikes to be perceived inferior to those associated with a low number of Dislikes as well as those without any Dislike-feature at all:
H3: Introducing a high number of Dislikes to
(a) a low number of Likes and no Dislike-feature
(b) a low number of Likes and a low number of Dislikes
(c) a high number of Likes and a no Dislike-feature
(d) a high number of Likes and a low number of Dislikes
has a negative influence on people’s perception of product quality

An overview of H2 and H3 is presented in Figure 2.

![Figure 2. The effect of Likes in conjunction with Dislikes on Perceived Quality (PQ)](image)

Methodology

One preliminary qualitative study and one experimental study were conducted to test the proposed hypotheses. In the absence of prior studies on the perception of Likes and Dislikes, the preliminary study was designed to (A) verify the rationale behind our hypotheses, (B) to select appropriate stimuli, and (C) to determine how to appropriately conduct treatment manipulation. The experimental study was designed to test our hypotheses on the effects of Likes and Dislikes on people’s perceptions of product quality.

Preliminary study

Subjects

The interviews and the focus group were conducted in July 2011. Participants were recruited via a student mailing list. All ten participants of the preliminary study were students between 19 and 32 years old (see Table 1 for demographics). All participants used Facebook on a regular basis.

<table>
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<tr>
<th>Table 1. Demographics of preliminary study</th>
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<tr>
<td>Interviewees</td>
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<td>3 / 2</td>
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<tr>
<td>Focus group participants</td>
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<td>Male/Female</td>
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<td>2 / 3</td>
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<td>Total</td>
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<td>5 / 5</td>
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Procedure

We conducted five semi-structured pilot interviews and one focus group session. The interviews and focus group session were conducted in a university facility in Germany. Interviewees and focus group participants were presented with mockups of websites of various products and services featuring varying numbers of Likes and Dislikes.

(A) In order to verify the rationale behind our hypotheses, we asked participants about their overall perception of the products. We then asked explicitly how the number of Likes and Dislikes relates to their evaluation. Following up on this question, we asked which amount of Likes and Dislikes would make a difference in their perception. Further, to verify two assumptions, we asked: Are you more inclined to ‘like’ a product or service if you appreciate its quality? Do you know of promotional campaigns which provide incentives to ‘like’ a product or service?

(B) In order to choose appropriate stimuli, participants were presented with a set of eleven preselected products and services with high pre-purchase information scarcity and the ability to detect the performance after the purchase (i.e., an experience good according to Nelson, 1970). Participants were asked to rank the products according to the following dimension; a need exists to reduce the perceived risk of purchase.

(C) In order to determine appropriate quantitative threshold levels for the experimental manipulation, we presented each stimulus in multiple versions featuring varying numbers of Likes and Dislikes. The numbers were derived from average numbers within the respective industry. For example, fast moving consumer goods may be sold nationwide and therefore, have more Likes as opposed to a local car dealer or restaurant. Rather than testing even levels such as 50, 100, or 200, we presented uneven number such as 41, 92, or 197 to make the numbers appear realistic. To determine what would be considered a high (low) number of Likes we checked for the highest number of Likes for which all participants agreed that it would have (no) effect on their product perception. To determine what would be considered a high (low) number of Dislikes we checked for the highest level of Dislikes for which all participants agreed that it would (not) have a negative impact on their product perception.

The transcripts of the interviews and focus group sessions served as the basis for our analysis.

Results

(A) All participants agreed to the following statement: “I do perceive user evaluations as valuable information for evaluating untested products.” Most (i.e., 7 out of 10) participants found Likes to be a genuine customer-to-customer evaluation signal. However, some (5/10) participants expressed concerns about the expertise of the people who ‘liked’ a product. All participants were aware of promotional campaigns to drive Likes and that marketers could create fake Facebook account to increase the number of Likes. All participants were aware that efforts to artificially drive Likes are costly for the marketer. Overall, the majority of participants (6/10) stated that Likes would have a (slight) positive impact on their perception of product quality. All participants agreed that they would be more likely to ‘like’ a product or service if they appreciate its quality. Regarding the effects of a Dislike-button all participants agreed that this feature would increase credibility. With respect to the overall effect participants agreed that a “high” level of Dislikes would definitely have a negative effect on their product quality perception.

(B) Ranking a set of eleven preselected products with respect to a need to reduce the risk of purchase all participants included the following products and services in their top three; an independent burger restaurant, a fictitious, non-branded water softener, and a second-hand car dealer.

(C) The highest (lowest) number of Likes to which all participants agreed that it would have (no) effect on their perception of the quality of a restaurant was 205 (998). The lowest (highest) number of Dislikes participants agreed that it would have an (no) negative effect on their perception of the quality of a restaurant was 48 (11). The results for the other stimuli can obtained from Table 3.
**Experimental study**

The experiment was designed to assess the influence of Likes and Dislikes on people’s perception of product quality. Participants were presented with screenshots of websites of various products featuring varying levels of Likes and Dislikes.

The experimental design allowed us to control for noise factors such as attributes of a website which can be a signal of product quality in itself (Wells et al. 2011). The setting did not require a payoff scheme or physical interaction among participants. This allowed us to run the experiment based on an online survey, rather than in a laboratory environment (Schade 2005). A total of three different stimuli were tested.

![Figure 3. Stimulus 1, Treatment X2 (left) Versus X4 (right)](image)

**Stimuli**

Signals convey information about unobservable product qualities. Therefore, we chose products and services for which consumers cannot readily observe the quality, i.e., experience goods. Even though products often involve a mix of search and experience attributes, an approximate distinction is important and widely accepted (Huang et al. 2009).

As a result of the preliminary study we chose the following stimuli to test our hypotheses:

1. An unknown burger restaurant. Consumers cannot tell whether the food served at a restaurant is good or bad before he or she tasted it. When people visit a restaurant they may infer from the smell of the food or the number of present customers how the quality may be. Such cues are not available to consumers who visit the website of a restaurant.
2. A non-branded water softener. Consumers can observe a water softener’s performance only after purchase and even then only after a long period of usage.
3. A second hand car dealer. Consumers lack the expertise to evaluate the quality of a second hand car prior to purchase.

In order to exclude noise factors we created a standardized template which was used for the design of the website screenshots. Each stimulus featured a picture of the product or service, the name, a “continue”-button as well as a Like-button and, depending on the treatment group, a Dislike-button. The Like-button was an exact replica of the original button, the design of the Dislike-button was based on the look of the original Like-button. Figure 3 shows an example.

**Treatments**

A total of 18 different interface treatments were developed to provide variation in Likes and pairs of Likes and Dislikes (Table 2) throughout all stimuli. Treatment manipulation was conducted by varying the number of Likes, adding Dislikes and varying the number of Likes combined with Dislikes. The values of Likes and Dislikes were based on the findings from the preliminary study (Table 3).
The treatment manipulation was varied across different experimental groups. Using a 2x3 factorial design allowed us to systematically control for six different combinations of Likes and Dislikes (Table 2). For example, participants in cell X2 were presented with a screenshot of the website of a burger restaurant featuring a Like-button that stated “998 people like this” while participants in cell X4 saw the exact same screenshot but with an additional Dislike-button stating that “11 people dislike this” (Figure 3).

The factorial design allowed us to control for interaction effects between the factor levels (Campbell and Stanley 1963), for example, whether an increase of the number of Dislikes has a different effect when the number of Likes is high versus low.

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<tr>
<th>Table 2. Treatment matrix</th>
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<tr>
<td>No Dislike-feature</td>
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<td>Low number of Dislikes</td>
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<tr>
<td>High number of Dislikes</td>
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<tr>
<th>Table 3. Overview of the experimental setting</th>
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<tr>
<td>Treatment</td>
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<tr>
<td>Stimuli</td>
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<td>(1) burger r.</td>
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<tr>
<td>(2) water sf.</td>
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<tr>
<td>(3) car deal.</td>
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**Measure**

For the manipulation check, the participants rated perceived product quality for each item on a 7-point Likert-scale. The measures were adapted from prior Signaling research (Boulding and Kirmani 1993): participants rated each item in both absolute terms and relative to market average. The two items were averaged to form a single overall scale.

**Subjects**

Participants were recruited via a multitude of mailing lists including; student mailing lists from various faculties, an alumni mailing list and a mailing list for IT professionals. As an incentive to join the experiment, a donation to a charitable project was made for each participant who completed the experiment.

In the period between the 4th and the 14th of September 2011, 1063 participants were recruited of which 40% dropped out during the experiment, resulting in 653 participants who completed the experiment.

70% of the 653 participants were female, 30% male. 80% were from Germany; the remaining 20% were from a set of 20 different nationalities. 11% of all participants were 20 years old or younger, 70% were between the 21-29 years old, 18% were between 30 and 40 years old.

**Experimental procedures**

Participants clicked a link, which sent them to a welcome screen. Here, participants were provided with a short description of the procedure. Participants stated gender, age and nationality. No further pre-tests
were applied. Then participants were randomly assigned to one of six treatment groups: X1, X2, X3, X4, X5, or X6 (i.e., between subject design according to Friedman and Sunder, 1994). Participants were not aware of the existence of other experimental groups. The products and services were fictional, but participants were told they were real.

Each participant was exposed to all stimuli, one per page. For example; participants in X1 saw the screenshot of the burger restaurant featuring 205 Likes, then the water softener featuring 710 Likes, and finally, the car dealer featuring 41 Likes. Participants in X5 saw the exact same screenshots but featuring 205 Likes combined with 48 Dislikes (burger restaurant), 710 Likes combined with 171 Dislikes (water softener), and 41 Likes combined with 9 Dislikes (car dealer). The order of the stimuli was the same throughout all treatment groups.

For each stimulus participants rated the quality they would expect. The results were used for the manipulation check.

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<th>Table 4. Descriptive Statistics</th>
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<td>Stimulus 1</td>
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<td>Treatment</td>
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<td>X1</td>
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<td>X5</td>
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<td>X6</td>
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Results

Descriptive statistics can be obtained from Table 4. The data showed no evidence of outliers, therefore no data transformations were performed. Hypothesis testing was performed using SPSS 17.0. All analyses were conducted with alpha set to 0.05. Manipulation checks were conducted using a 3 (levels of Dislikes) X 2 (levels of Likes) within-subjects ANOVA. ANOVA is the standard procedure to detect treatment effects for a metrical dependent variable and independent variables on nominal scale (Backhaus et al. 2012). Bonferroni corrections were applied to the post-hoc pairwise comparisons for X1/X3/X5, as well as X2/X4/X6. For results with p-values between 0.05 and 0.10 a complementary t-test was applied and if rendered significant, i.e., p-value < 0.05, indicated explicitly (°). Binary dummy regressions were conducted to determine the direction and strength of significant effects of variations in the number of Likes and Dislikes compared to the baseline conditions (i.e., X1 and X2). All results are presented in Tables 5 through 10.

Participants who were exposed to treatments featuring a high number of Likes (X2) perceived the quality of the stimuli significantly higher than those who saw the same stimulus but featuring a low number of Likes (X1). This result could be replicated throughout all stimuli (p-values < 0.05, β-values > 0). Therefore, the results support H1: in the absence of a Dislike-button, increasing the number of Likes has a positive effect on perceived product quality.

Across all stimuli adding a low number of Dislikes (X3) to a low number of Likes (X1) had a significant (p-values < 0.05) positive (β-values > 0) effect on participants’ product quality perception, thus, supporting H2a. The results did not support H2b though: adding a low number of Dislikes (X4) to a high number of Likes (X2) did not have a significant positive effect on the product quality perception (p-values = 0.727 / 0.150 / 0.389). This means adding a low number of Dislikes has a significant positive effect only when the number of Likes is low. This speaks for an interaction effect, in that the effect of Dislikes depends on the baseline level of Likes.

The results did not support H3: Across all stimuli, adding a high number of Dislikes (X5, X6) did not have a negative effect on product quality perception of the participants. Instead, adding a high number of
Dislikes (X5) to a low number of Likes (X1) even had a significant positive effect on quality perceptions of stimulus 2 (p-value < 0.05 with separate t-test, β > 0) and stimulus 3 (p-value < 0.05, β > 0).

Interestingly enough, perceived quality did not significantly differ (p-values = 0.296 / 0.668 / 0.448) whether a product was associated with a low number of Likes combined with a low number of Dislikes (X3), or whether it is associated with a high number of Likes (X2).

<table>
<thead>
<tr>
<th>Table 5. ANOVA and Bonferroni Post-Hoc-Tests for Stimulus 1</th>
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<tbody>
<tr>
<td>combination</td>
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<tr>
<td>X1 and X2</td>
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<td>X5 and X6</td>
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<td>X2 and X4 and X6</td>
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**significance levels: *** < 0.001, ** < 0.01, * < 0.05, ° < 0.05 (separate t-test)**

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<th>Table 6. Dummy Regression for Stimuli 1</th>
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<td>reference category</td>
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<td>X1</td>
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<td>X4</td>
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<td>X5</td>
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<td>X6</td>
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**significance levels: *** < 0.001, ** < 0.01, * < 0.05**

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<tr>
<th>Table 7. ANOVA and Bonferroni Post-Hoc-Tests for Stimulus 2</th>
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<td>X1 and X2</td>
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<td>X3 and X4</td>
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<td>X5 and X6</td>
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<td>X2 and X4 and X6</td>
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**significance levels: *** < 0.001, ** < 0.01, * < 0.05, ° < 0.05 (separate t-test)**

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<thead>
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<th>Table 8. Dummy Regression for Stimulus 2</th>
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<td>X1</td>
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<td>X4</td>
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<td>X5</td>
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<td>X6</td>
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**significance levels: *** < 0.001, ** < 0.01, * < 0.05**

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Table 9. ANOVA and Bonferroni Post-Hoc-Tests for Stimulus 3

| X1 and X2 | 0.022 | 4.924 | 0.028* | - |
| X3 and X4 | 0.000 | 0.009 | 0.925 | - |
| X5 and X6 | 0.006 | 1.301 | 0.255 | - |
| X1 and X3 and X5 | 0.027 | 4.395 | 0.013* | - |

significance levels: *** < 0.001, ** < 0.01, *< 0.05, ° < 0.05 (separate t-test)

Table 10. Dummy Regression for Stimulus 3

| X1 | X2 on PQ | 0.299 | 0.028* |
| X3 on PQ | 0.404 | 0.005** |
| X4 on PQ | 0.417 | 0.003** |
| X5 on PQ | 0.273 | 0.047* |
| X6 on PQ | 0.432 | 0.002** |

significance levels: *** < 0.001, ** < 0.01, *< 0.05

Discussion

This research is inherently interdisciplinary, using insights and methodologies from IS as well as marketing and psychology. We are able to show how the innovative use of IS can change people's perceptions of products and services. Our results confirm the immense economic impact of IT, underlining IT's new strategic role. These results may also be of use to practitioners, helping them to optimize the use of Like- and, potentially, Dislike-buttons and to develop variations of those classical themes.

Theory Implications

On a general note, the present work shows that Signaling provides a valuable framework for studying the effects of design decisions in computer-mediated communication. Specifically, the results show that the theoretical framing of Likes as a signal is valid. Likes do have a significant influence on people's perception of product quality. Therefore, brands and sellers can use this feature "to convey information credibly about unobservable product quality to the buyer" which is the very definition of a signal (Rao et al. 1999, p. 259).

Our findings on the effect of Dislikes contribute to the research on two-sidedness. With respect to negative customer reviews on the Internet, research has focused on the effect of varying amounts of negative information (e.g., Lee at al. 2006). To the best of our knowledge, there have been no studies on the effect of adding negative information to a baseline scenario without (allowing for) any negative information at all. This is an important distinction as research on negative customer reviews may be misleading as it only shows negative effects for brands and merchants. Our results show that allowing for negative information actually improves people's quality expectations. In line with findings from marketing research, we find that adding a low amount of negative information to a low amount of positive information leads consumers to expect higher quality. This may seem counter-intuitive, but is well explained by the theoretical framework we applied: Signaling builds on credibility. Exposure to Dislikes, i.e., negative information, creates credibility, thus, strengthening the positive effect of Likes, i.e., positive information.

However, too much negative information may alleviate the positive effect on people's quality expectations: Introducing a high number of Dislikes had a positive effect just in the case of two stimuli and only under
particular conditions, i.e., only given a low number of Likes and only when compared to a scenario with no Dislike-feature at all. Other scenarios showed either no effect, or a negative effect of introducing a high number of Dislikes. This suggests that negative information has two diametrical effects: (1) It amplifies the influence of positive information by adding credibility, and (2) it exerts a direct negative effect on people’s quality expectations.

**Practical Implications**

So what does it mean for brands to include Facebook’s Like-feature on their website? Do Likes influence the perception of consumers? Yes, they do. Whether you are a burger restaurant, a second hand car dealer, or a producer of a water softener: Likes are a signal of product quality. And consumers’ perception regarding product quality is what drives sales (Well et al. 2011). The impact of Likes is not just marginal: In our sample, increasing the number of Likes lead to a plus of 6% to 10% in perceived quality. Achieving an effect of this magnitude may be very expensive to achieve otherwise. Therefore, brands should include Likes as a Key Performance Indicator (KPI) for marketing campaigns.

Focusing solely on increasing the number of Likes may not be necessary though. Our results show that adding a low number of Dislikes leads to the same effect, i.e., the perceived quality does not significantly differ whether a product is associated with (1) a low number of Likes combined with a low number of Dislikes or whether it is associated with (2) a high number of Likes combined with no Dislikes. For example, adding 793 Likes to the website of a burger restaurant lead to 6% higher quality perception in our sample while adding 11 Dislikes instead lead to a 10% increase. Perhaps including Dislikes would be cheaper than boosting the number of Likes through investments in actual product quality or incentives for consumers to 'like' a product. For now, Facebook does not offer a Dislike feature though. This means marketers have to be creative and try out other ways of exposure to negative information.

Meanwhile, if a product is already associated with a high number of Likes, adding Dislikes does not significantly influence people’s perception of product quality. For brands which already have a high number of Likes associated with their products, this means that they would not need to fear negative feedback. At the same time, it means an opportunity for small online merchants who may have limited exposure and low numbers of Likes associated with their products. Consequently, increasing the number of people who ‘like’ their products may require costly marketing investments. Adding negative information may achieve the same effect at a fraction of the costs.

Arguably, the reason why Facebook has not implemented a Dislike-button in the first place is to not scare brands away from the platform. In a social network where opinions spread quickly amongst so many people, the image of a brand or product may be destroyed. Certainly, it is in Facebook's interest to attract more brands (and, potentially, advertisers) by making design choices that minimize the risks for brands which join the platform. With respect to people’s perception of product quality, our results indicate that Dislikes do not hurt big brands (with high amounts of Likes) and that small brands (with small number of Likes) can actually benefit from Dislikes. This may encourage Facebook, or challengers such as Google's “Plus 1” button, to allow for negative user feedback.

**Limitations and future research**

As with all experimental research, external validity is potentially limited. By testing each hypothesis across three different stimuli we could improve the generalizability. At the same time, the procedure may cause an order effect, in that participants may have been influenced by the order in which the treatments were presented. We focused solely on experience goods. An interesting avenue for future research is to contrast our results against findings from a study featuring novel products with more experiential attributes as well as search goods. For the latter, we would expect no significant influence of Likes and/or Dislikes as—by definition—there would be no need to reduce pre-purchase uncertainty by communicating unobservable product qualities.

It was the scope of this research to investigate whether Likes are a signal of product quality. While we could show that more Likes lead to significantly higher quality expectations, further research is needed to quantify the effect of various levels of Likes. The same applies for Dislikes and combinations of Likes and Dislikes: While businesses might be interested in the “golden ratio” of Likes and Dislikes, further
investigation of the effects of Dislikes will be interesting from a theory standpoint. In the absence of a Dislike-button we derived what would potentially be a low versus high number of Dislikes from a qualitative pre-study. Particularly, the effect of higher amounts of Dislikes on credibility and overall perception of product quality deserves further study.

There may be other explanations for the positive effect of Dislikes on people's quality perceptions. Within the framework of Signaling Theory, we explained the effect by added credibility. It is a limitation of our study that we cannot make specific statements about the underlying forces that lead to the positive effect of Dislikes. Future studies should further investigate underlying forces that lead to a positive net-effect of low amounts of Dislikes.

This study looked at the Like feature as it appears outside the Facebook platform. The applicability of our results of the effect of Likes for Pages on the Facebook platform needs to be tested. Also, this study looked at the effect of Likes and Dislikes on people's product quality perception. It will be interesting to investigate the effect on other variables. For example, do people agree more with an opinion if a corresponding article was 'liked' a lot?

**Conclusion**

Do Likes influence the perception of consumers? Going back to the initial research question, we can definitely state that Likes serve as a signal of product quality: if a product or service was 'liked' a lot, then people will attribute a higher quality to it. Further, we find that adding a Dislike-button can have the same positive effect; if the number of Likes is low, displaying a low number of Dislikes will lead to higher quality expectations. A high number of Dislikes will have no negative effect on people’s quality expectations.

As of today, 1,692,671 people joined the Facebook group "PETITION FOR FACEBOOK TO INSTALL A DISLIKE BUTTON" – one of the largest groups on Facebook. Clearly, there is a demand for a Dislike-feature. The results show that there is an opportunity for brands in extending the concept of Likes towards a two-sided signal.

**References**


