Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

The Effect of Positive and Negative Signals on Perceived Deceptiveness of Websites in Online Markets

Tamilla Mavlanova[1], Raquel Benbunan-Fich[2], Marios Koufaris[3], and Guido Lang[4]

[1] University of Connecticut, School of Business, Department of Operations and Information Management, Stamford, CT, USA tamilla.mavlanova@business.uconn.edu
[2] Baruch College, CUNY, Zicklin School of Business, Department of Statistics and Computer Information Systems, New York, NY, USA rbfich@baruch.cuny.edu
[3] Baruch College, CUNY, Zicklin School of Business, Department of Statistics and Computer Information Systems, New York, NY, USA marios.koufaris@baruch.cuny.edu
[4] Quinnipiac University, Department of Computer Information Systems, Hamden, CT, USA guido.lang@quinnipiac.edu

Received 09 July 2013; received in revised form 24 December 2013; accepted 02 January 2014

Abstract

This study extends the understanding of signaling in online shopping environments by evaluating the effect of positive and negative signals on perceptions of online buyers. Drawing from signaling theory, this study proposes and empirically tests a model for conceptualizing the influence of website signals on perceived deceptiveness and purchase intentions. The results support the assertions of the model and indicate that the online buyers' perceptions of website deceptiveness and purchase intentions are mainly influenced by website content, website amateurism and website physical presence, whereas human presence is not significant.

Keywords: Signaling theory, Website signals, Deception, E-commerce, Purchase intentions

1 Introduction

When physical stores increase their investments in property, personnel and inventory, they send a signal of quality and longevity to consumers. Unlike physical stores, online stores cannot provide such complete information about their quality and the quality of their offerings. Instead, they communicate this information virtually via their website's design, content, and experience. In other words, online sellers choose what information to provide to consumers via an online storefront and online buyers interpret this information and make their purchase decisions.

In order to better understand this process, we conducted a study using signaling theory, which is used in situations when two parties have access to different information. The signaler has a choice of how and when to communicate information using signals, while the receiver has a choice of how to interpret these signals [52].

Signals are rarely seen in isolation. Usually, signals are embedded in the environment surrounding them. Environmental distortion takes place when the medium for spreading the signal changes the ability to observe the signal. Therefore, receivers may or may not notice certain signals, or may have a different opinion regarding signals when some other signals are present. While previous studies on signaling evaluated the effect of isolated signals, there is a gap in the literature regarding how receivers group signals to form their opinions and decisions [15]. The contribution of this study is to focus on the receivers' perceptions of groups of signals in the online environment.

Signaling theory is used as a framework in this study to understand the way users interpret signals. The general assumption of signaling is that signalers focus on the deliberate communication of positive information to signal receivers. Signalers do not intend to send negative signals but occasionally negative signals can be an unintended consequence of the signaler's actions. Signals that are not intentional have been ignored in the literature. When signalers send signals without being aware of them, these signals could conflict with intentional signals or could communicate negative information about the signaler. As of now, there is little empirical research on negative signals and how they are different from other signals [15]. This study attempts to close this gap in IS research. We are using signaling theory to investigate which type of signals can reveal the true nature of a seller. While evaluating a website, users process multiple signals together. Some signals can lead to a positive perception of a website and some signals can lead to a negative perception. Thus, a significant contribution of this study is the consideration of negative signals in addition to positive ones.

Signals can be truthful or false. False signaling can lead to opportunistic behavior that motivates deceptive strategies initiated by unscrupulous sellers. In online markets, deception opportunities arise because of the geographic distances between sellers and buyers, their low level of familiarity with each other, and the limited number of interactions [54]. While trust [23], [30], [32], [33] and distrust [5] were discussed in e-commerce research, there is a lack of studies discussing signaling and deception. This study addresses this issue by evaluating the effect of signals on perceived deceptiveness of websites.

The study reported in this paper focuses on how website signals impact the buyers' perceptions of website deceptiveness and their purchase intentions. The study is centered on the pre-purchase phase of the shopping experience and on signals that appear during this phase. Hypotheses about buyer perceptions and purchase intentions are empirically tested with actual websites in which the users' perceptions of signals are evaluated.

With this research, we provide several theoretical and practical contributions to the literature on website signaling and we attempt to shed light on the issue of buyers' perceptions of website signals. At the theoretical level, we apply and expand signaling theory by using groups of signals instead of isolated signals; by evaluating the role of positive and negative signals; and by assessing the effect of signals on perceived deceptiveness of online storefronts.
The research question that motivates this study is:

How do buyers' perceptions of positive and negative signals affect perceived deceptiveness of a website and purchase intentions during the pre-purchase phase of online shopping?

To answer this question, a research model is developed and tested with an empirical survey based on the evaluation of three pharmaceutical websites of varying quality by 319 participants.

The rest of the paper is structured as follows: First, we introduce signaling theory and deception that are used to support hypotheses regarding the relationships between website signals and website deceptiveness, and eventually purchase intentions. The next sections introduce the research model, the description of research methods, analyses and the explanation of results.

2 Background

The following sections will introduce key concepts of signaling theory, deception and deception tactics that may occur in online commerce.

2.1 Signaling Theory

Signaling theory [52] investigates types of signals and the circumstances in which these signals are used. This theory has been applied in information economics to describe market interactions in which different parties have asymmetric information [7], [52]. Because some information is private, information asymmetries occur between those who own the information and those who could possibly make better decisions if they had access to this information [15]. In seller-buyer relationships, information asymmetry is characterized by the inability of the buyer to precisely evaluate the product or service quality prior to purchase [42], and it is based on the principle that the buyer and seller have different amounts of information regarding the products and services and disincentives to share this information [1]. The seller is motivated to sell a product as high-priced as possible, and the buyer is motivated to buy a high quality product at the lowest possible price.

Key concepts of signaling theory are a signaler, a signal, and a receiver [15]. A signaler chooses what information to display and in what form. Signalers use signals to communicate information. A signal is a cue that communicates certain unobservable quality of a person or a product to a receiver. A receiver is a person, or an organization that receives a signal and chooses how and in what way to interpret this signal.

The credibility of signals is achieved at a cost. Spence [52] suggests that signals are more credible when it is costly to produce a signal or if there is a high cost of punishment in case a false signal is discovered. Thus, high costs serve as a mechanism to prevent the usage of false signals.

Signaling theory has been used in the fields of economics, marketing, and information systems. In economics, the implications of signals such as cost [52], warranties [52], price [41], and advertising [41] have been discussed. Marketing researchers experimentally tested consumer side implications of signaling theory [7], the effects of brand name, price, physical appearance, and retailer reputation on seller quality [17]. They have also created a typology of signals based on the monetary consequence of a signal inferred by the firm, the sale contingency of a signal, and the risk of future consequences in case a signal is false [34]. In addition, the effects of brand [19], retailer reputation [14] and store environment [3] have been studied. In Information Systems research, the issue of signaling has been discussed in the areas of strategic signaling [58], offshore outsourcing [22], and software service provider markets [4]. Signaling theory has been used in the context of online commerce to investigate how reputation, warranties, perceived website investment and advertising expenditures influence trust and perceived risks with an online retailer [6], [47], [50], [55], and to evaluate the role of website quality as a signal of product quality [56]. Unlike previous studies, our research aims to assess the role of positive and negative signals on perceived deceptiveness of a website.

Signals that have been studied in online commerce include technological characteristics of websites, website design features, product presentation, website trust features, website policies and website content [21], [26], [32], [33], [38], [40], [43], [47], [48], [51]. For the purpose of this study, we consider signals as website features that are displayed on a website to convey information to a buyer. We consider both positive and negative signals and evaluate the buyers' perceptions of signals that are most likely to influence perceptions of deceptiveness as well as purchase intentions. These perceptions are based on website amateurism, website content, and physical and human presence [21]. In this study we test only perceptions of internal signals that are provided directly by a seller, while external signals, such as third-party verification seals or the information about the website or seller displayed on external websites are omitted.

To classify signals, we used an established framework of website content and design, which proposes that providing information is the basic goal of a website [29]. The more useful information the website has, the more valuable it is for receivers. Signals that form a perception of an informative content include the availability of customer reviews, shopping advice, articles, product information, and website policies.

Website design is a structure according to which web pages are linked to each other and information is displayed [29]. As the majority of websites use pre-existing templates for design, many online storefronts have similar designs and features. Because online buyers are used to a certain degree of quality and professionalism while shopping online, websites that do not maintain quality and that seem amateurish will stand out. Typographical errors, broken links, unexpected site unavailability, links to bogus websites and non-matching domain and company names are signals of an amateur design of a website [21].

In addition to content and design, we consider perceived physical presence of a website as a sign of signaling costs. Physical presence informs a buyer that the store exists not only in a virtual world but also in a real world. The real world feel of websites increases credibility of online stores [21]. A physical address, a store locator, and phone and

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

email information are signals that communicate a real world presence [21]. Some of these signals such as a physical address and store locator are related to physical objects such as buildings. Buildings are known to be expensive to own or rent. Therefore, according to signaling theory, these signals can be perceived as costly and more reliable. Human presence on a website is equally important and is based on signals such as human pictures and live chat [21]. Social signals such as links to Facebook or Twitter can also increase human presence on a website.

As signals are observable characteristics of an object that can be manipulated [52], they can be either truthful or not. When signals are truthful, both sellers and buyers benefit from them. When signals are false, it hurts buyers who may believe that a signal is true and may lead buyers to become a victim of a dishonest seller. It also hurts other honest sellers because when surrounded by fake signals, buyers may decide to ignore or misinterpret signals. As perceptions of signals are subjective, some signals may increase or decrease the perceived deceptiveness of a website. In the next section, we will discuss deception, and the effect of signals on the perceived deceptiveness of websites.

2.2 Deception

Deception is an intentional attempt designed by a deceiver to influence the behavior of a target [31] and is accomplished by manipulating the information provided [57]. Turner et al. [53] propose that information can be manipulated through concealment and distortion. This proposition is consistent with Ekman [18], which suggests that the two major deception strategies include concealment and falsifying. In concealment, the deceiver withholds or omits some information without saying anything untrue. In falsifying, the deceiver presents false or exaggerated information as if it were true. The concealment tactic is often preferred, as it does not require any additional resources to make up a deceptive story. When signaling, concealment tactics are less costly for the sellers, as nothing has to be invented to cover deception.

In online commerce, deception is mostly related to the conflicts of interest between a seller and a buyer especially in situations when financial transactions are involved [25]. Online deception can result in opportunistic behavior on the seller side such as fraud, unauthorized collecting and selling of buyer private information, failure to acknowledge a refund, the delivery of inferior products, delayed delivery, or no delivery at all [24], [44].

Perceived deceptiveness of a website is based on its design and content. Xiao and Benbasat [57] identify types of deceptive techniques that are specific to online commerce - the manipulation of information presentation and generation, and the manipulation of information content. Information presentation and generation refer to the way information is displayed on the website both on static and dynamic webpages. Information can be presented via text, graphics, audio, video, animated content [37], and virtual experiences [57]. It can be generated via search engines, product catalogs and recommendation agents [57]. The manipulation of information content can be achieved by manipulating the way the information is organized on the website as well as by misrepresenting product attributes [57].

Dishonest online sellers will engage in deceptive tactics, as long as they do not incur any additional expenses, in order to extract maximum benefits out of their questionable practices. Since in most instances exaggeration can lead to additional expenditures, deceptive sellers will tend to conceal information, which is a less expensive approach. In online commerce, information is provided via web pages that display information content. Thus, sellers have two ways to deliver information: website design and content. If the sellers choose to employ concealment tactics, then they will not add anything to the existing website design and will not update the website content often. Thus, buyers may perceive their websites as amateurish websites with little or low quality content.

3 Hypotheses Development

Figure 1 summarizes hypotheses 1-5 and presents our research model. The basic premise of the model is that perceived website amateurism positively affects perceived deceptiveness (H1), perceived content, perceived physical and human presence negatively affect perceived deception (H2-H4) Perceived deceptiveness decreases purchase intentions (H5).

Signals can be unintentional and negative [15]. Unintentional signals can send negative information to receivers and disturb the signaling process in such a way that signals serve a negative role.

Amateurism of a website is a signal that is inferred from the information presentation on the website and may be based on small errors, broken links and website glitches [21]. Amateurism can be the result of fraudulent intent or incompetence of a seller [16]. From a buyer perspective, buyers are affected by amateurish websites in both cases equally. Thus, it is important to distinguish between amateurism that arises from fraudulent intent and amateurism that results from incompetence. The distinction between these two concepts lies in the costs of reducing fraud or incompetence, or the costs of reducing deliberate misrepresentation and increasing the quality of information on the part of a seller [16]. Therefore, amateurish websites can be due to more than simple incompetence: it could be part of a seller strategy to save time and effort, which can be the origin of much fraud.

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

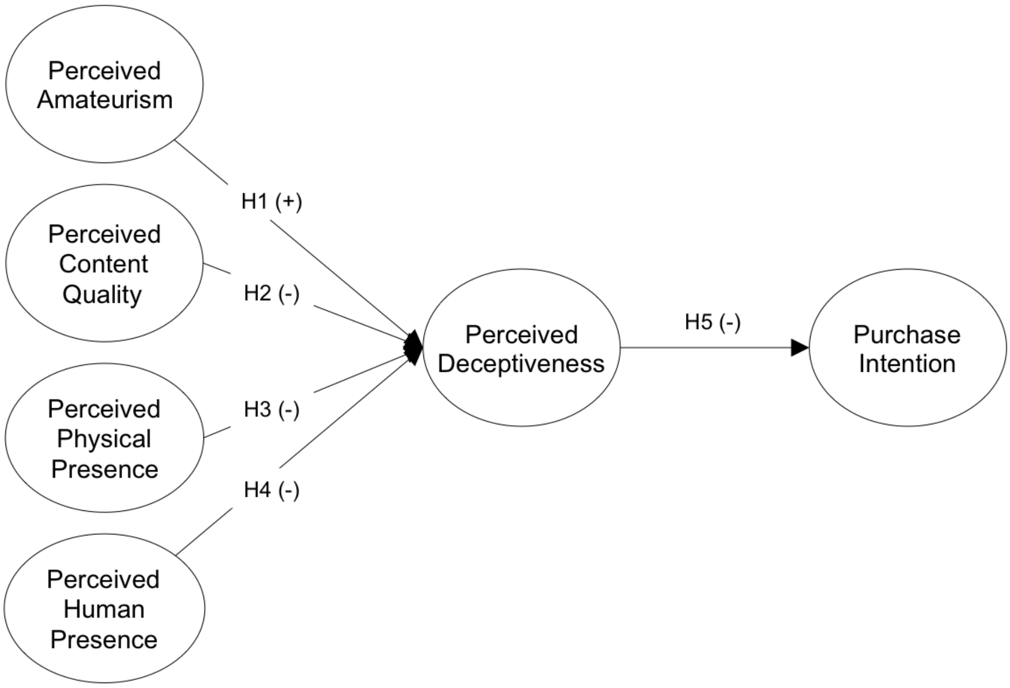

Figure 1: Research model

Absence of professionalism on the part of the seller is a signal of the seller's unwillingness to spend resources in the professional design of its website. This is consistent with the deliberate attempts of fraudsters to reduce costs in order to maximize the profitability of their fraudulent endeavors. Thus, amateurism may raise concerns about the deceptiveness of a website. Although the quality of a website does not change the quality of products on the website, website quality influences purchase intentions [20], and amateurish-looking websites may negatively influence buyer perceptions.

Buyers that encounter imperfections on the website may believe that the absence of professionalism on the part of the seller is a signal of the seller's incompetence or fraudulent intent. Thus, amateurism in websites may serve as a signal of website deceptiveness.

H1: Perceived website amateurism positively affects perceived deceptiveness of a website.

Deceptive strategies are often accompanied by the manipulation of information content [10]. In online stores the content can be concealed or falsified. For example, an online seller can withhold negative information about the product or exaggerate positive information on the website [57]. Content signals may include product information, expert product reviews, press releases, frequently asked questions (FAQ), and news. Richer information content of a website is one of the most vital signals influencing perceptions of the overall quality of the website [26]. Huizingh [29] defines the perception of content as highly valued by online users and states that a high-quality website should provide specific and extensive product and company information as well as other information on topics relevant to the company's mission.

In a similar vein to website amateurism, sellers may increase the level of quality of information that is provided on a website based on their will. However, the increase in the level of quality requires investment of real resources both in labor and goods [16]. At the same time, not providing appropriate valuable content on a website involves no additional resources, and maximizes profits of fraudulent sellers.

Low quality in the information content of a website is a signal of the seller's reluctance to invest time, effort and resources in providing information. By providing detailed information, fraudulent sellers are not incurring additional expenses but they are also increasing the likelihood of being discovered if the information is inaccurate. Therefore, this type of sellers will refrain from providing high quality content and prospective buyers will associate the lack of content with deception.

The lack of accurate, updated and sufficiently detailed content may prompt buyers to believe that a seller has something to hide and uses a concealment deception strategy by not disclosing enough information or not providing enough useful content. However, if the perception of the content is positive, the website may be considered to be informative. Thus, we hypothesize a negative relationship between website content quality and perceived deceptiveness of a website.

H2: Perceived website content quality negatively affects perceived deceptiveness of a website.

The main tenet of signaling theory is signaling cost [52]. The more expensive the signal, the more valuable it is for receivers. Physical store presence signals, such as a store locator, convey longevity and stability for a website as they show that a solid monetary investment has been made for the development of physical stores.

Likewise, comparable signals such as listing the organization's physical address and other contact details have been found beneficial for the perception of website credibility [21].

Perceived physical presence may increase the perception of website longevity (i.e. the feel that the online store will stay in business longer), and reinforce the belief that the seller will not go out of business shortly. Physical store presence serves as a signal of a store's financial security and provides assurance that the store is a real establishment [32]. Hence, we propose:

H3: Perceived physical presence negatively affects perceived deceptiveness of a website.

Human presence signals increase the presence of human touch in online environments. In virtual online marketplaces, it is important to provide human related signals such as pictures of people or live chat technology to increase the feel that real people work behind a virtual store representation. Fogg et al. [21] found that displaying images of organization members on a website increases the website's credibility.

Social signals such as Facebook or Twitter may add to the feeling that real people use the website as users tend to perceive social networks not only as technology but as quasi-people [36]. If buyers believe that real people are behind the website, they are likely to experience lower perceived deceptiveness of the website. Therefore, we propose:

H4: Perceived human presence negatively affects perceived deceptiveness of a website.

The theory of deception by Johnson and colleagues [31] explains intentional deception from both the deceiver's and the target's points of view. A deceiver is aware of processes that targets use to interpret information: 1) target looks for information in the environment; 2) target evaluates the information; 3) target makes a decision. Then, the deceiver manipulates the environment to mislead a target and force the target to believe that certain misrepresented facts are true.

The target may be able to detect deception by telling the difference between their expectations and the deceiver's manipulation. If the target does not have enough knowledge or experience in the domain in which the deception is likely to occur, the deceiver may succeed. On the contrary, if the target sees the difference between their expectations and the deceiver's manipulation, the target may refrain from dealing with the deceiver.

Thus, the willingness to transact with the seller will be determined by the consumer's appraisal of the website and its content. If deception is suspected, buyers will refrain from making a purchase. Therefore, the following hypothesis is formulated.

H5: Perceived deceptiveness of a website negatively affects purchase intentions.

4 Methodology

To test our research model, a between subjects design was employed. The participants were asked to evaluate existing online pharmacies. Online pharmacies were used in this study as it was relatively easy to obtain the information about the quality of online sellers from the industry associations. 120 pharmacies were randomly selected based on the guidelines of the National Association of Boards of Pharmacy (NABP) and LegitScript, a verification and monitoring service for online pharmacies. The quality of the online pharmacies was assigned based on the NABP and LegitScript recommendations that are based on the quality of medicines, safekeeping of patient records, proper licensing etc. Based on the results of a content analysis of signals available on the selected websites, three websites were selected for the study. All websites were actual online retail pharmaceutical websites representing three groups of online sellers: online only/high quality, click-and-mortar/high quality, and online only/low quality. The selected websites were the most representative of each profile suggested by NABP and LegitScript.

Task. In order to establish a common task context, all participants were given a scenario according to which they had to examine website content and design and make a purchase decision on behalf of an imaginary person. The participants were asked to locate a specific medicine for an elderly person who had neither a physical ability to go to an actual pharmacy nor the internet skills to make an online purchase. To complete the task, participants were asked to 1) to evaluate the website by examining the store's design and content; 2) to locate a specific product; 3) to make a purchase decision; 4) to complete a post-test questionnaire. The participants in all conditions were asked to search for the same type of medicine that was available on all three websites.

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

Measures. The post-test questionnaire used measures adapted from existing scales for (a) perceived website amateurism [21]; (b) perceived website content quality [26]; (c) perceived human presence [23]; (d) perceived physical presence [21]; (e) purchase intentions [23].

Subjects. Students enrolled in the introductory IS undergraduate course at an urban U.S. university in the Northeast participated in the study. Each study participant was randomly assigned to evaluate one of the three websites. In total 319 responses were collected with 104, 108, and 107 participants in each condition (online only/high quality, click-and-mortar/high quality, online only/low quality). Students received course credit for their participation. The participation was voluntary with alternative options for course credit available.

5 Results

The following sections will introduce the results of website coding and hypotheses testing, as well as the results of structural equation modeling analysis.

5.1 Website Coding

The three websites selected for the study provided a range of over-the-counter and prescription-only medicines. All websites had a similar navigability including search and browsing features. In addition, all websites provided images and descriptions of their products, as well as recommendations on how to use them and possible side effects. All websites displayed privacy, security and return policies.

Three independent researchers coded signals in the three selected online pharmacies. The inter-coder reliability, computed as the percent of agreement obtained for all variables, ranged from 85% to 100%, showing a high level of reliability for all signals. Coding disagreements were adjudicated by discussion and consensus and a joint examination of the feature in question.

Amateurism, content, physical presence and human presence were coded based on the presence or absence of signals (See Appendix A). The results of the coding are displayed in Table 1.

Table 1: Total number of signals in selected websites

	Amateurism	**Content**	**Human Presence**	**Physical presence**
High Quality Online Only	1 (20%)	5 (100%)	2 (50%)	3 (75%)
High Quality Click-and-mortar	0 (0%)	4 (80%)	4 (100%)	4 (100%)
Low Quality Online Only	2 (40%)	2 (50%)	2 (50%)	1 (25%)

Note: % of total number of signals possible in our sample is shown in parentheses

The results of the coding indicate that there are differences between the click-and-mortar seller and online-only sellers in terms of amateurism. In other areas, high quality websites (online only and click-and-mortar) displayed more content, more human and physical presence signals than the low quality/online only website. The coding procedure thus offers a more concrete view of how signals are employed by sellers of varying quality in our study.

5.2 Hypotheses Testing

The sample consisted of 319 participants with 104, 108, and 107 subjects per condition. About half of the participants (167, 52.4%) were females. The majority (83%) of participants were between 18-25 years old and 17% of participants were between 26-35 years old.

We used structural equation modeling (SEM) to analyze the data. Specifically, we used lavaan package version 0.5-11 [49] implemented in the R system for statistical computing [46]. The R package lavaan provides a free, open source and high quality alternative to commercial SEM software [49] with similar functionality.

Following the recommendation for the analysis of models with structural and measurement components outlined in [35], we adopted a two-step modeling procedure [2]. In two-step modeling, the model is first specified as a confirmatory factor analysis measurement model. The measurement model is then analyzed to assess overall model fit as well as reliability, convergent validity, and discriminant validity of the constructs. Upon acceptance of the measurement model, the model is re-specified as a structural regression model. The structural model is then analyzed to assess overall model fit as well as the significance and strength of the hypothesized structural paths.

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

5.3 Measurement Model

To assess the measurement model, we conducted a confirmatory factor analysis. Selected fit indices of the initial measurement model indicate poor overall fit: X2(309) = 1164.998, p > .05, comparative fit index (CFI) = .821, Tucker-Lewis index (TLI) = .796, normed fit index (NFI) = .773, non-normed fit index (NNFI) = .773, goodness of fit index (GFI) = .969, adjusted goodness of fit index (AGFI) = .959, standardized root meant square residual (SRMR) = .078, and root mean square error of approximation (RMSEA) = .093 with the 90% confidence interval .088 – .099. A closer inspection of the constructs revealed several items with low factor loadings (i.e. fully standardized loading of less than .7). Not surprisingly, the vast majority of items with low loadings are reverse-coded questions. This suggests that subjects in the study might have potentially misread or overlooked the negative wording of these items. This problem is not uncommon in applied research [8]. The majority of regular items in the perceived amateurism scale exhibit low standardized loadings, ranging from .133 to .781. However, it is important to note that the perceived amateurism scale already exhibited low loadings and a Cronbach α of .64 in the original scale development and validation study [20]. Thus, we recognize that the perceived amateurism scale has deficiencies. To improve the initial measurement model, we decided to remove the lowest-loading items in the constructs under study. As a result, we are left with three perceived deceptiveness items (out of six), three amateurism items (out of six), three content quality items (out of four), two human presence items (out of three), and three physical presence items (out of five). The list of final items and constructs in the revised measurement model is shown in Table 2.

Table 2: Item loadings and construct reliability

Construct	Item	Mean	SD	Std. Loading	Z-Value	Cronbach's α	AVE
Purchase Intention (PI)	PI1	3.75	1.887	0.832	17.619	0.838	0.639
	PI2	4.52	1.979	0.853	18.304		
	PI3	3.99	1.926	0.705	13.903		
Perceived Deceptiveness (DE)	DE1	2.72	1.480	0.914	20.627	0.872	0.709
	DE3	2.83	1.467	0.876	19.274		
	DE5	2.94	1.553	0.724	14.565		
Perceived Amateurism (AM)	AM3	3.28	1.346	0.540	9.111	0.667	0.414
	AM5	3.28	1.592	0.772	13.491		
	AM6	3.63	1.465	0.595	10.196		
Perceived Content Quality (CQ)	CQ2	4.96	1.469	0.799	16.711	0.874	0.707
	CQ3	4.92	1.622	0.843	18.140		
	CQ4	4.85	1.556	0.878	19.318		
Perceived Human Presence (HP)	HP1	4.05	1.662	0.743	12.374	0.735	0.583
	HP2	3.58	1.562	0.783	12.932		
Perceived Physical Presence (PP)	PP1	4.12	1.955	0.708	13.390	0.801	0.588
	PP2	4.12	1.955	0.711	13.454		
	PP3	3.74	2.146	0.871	17.353		

Note: AVE = Average Variance Extracted

After removing the aforementioned items, the measurement model converged to an admissible solution and values of selected indices suggest good overall model fit: X2(104) = 224.472, p > .05, CFI = .960, TLI = .947, NFI = .928, NNFI = .947, GFI = .994, AGFI = .989, SRMR = .051, and RMSEA = .060 with the 90% confidence interval .049 - .071. Although the chi-square statistic is significant, the ratio of chi-square to degrees of freedom is 2.158, well below the suggested maximum of 3 [12]. Moreover, values of the CFI, TLI, NFI, NNFI, GFI, and AGFI are all above the suggested threshold of .9 [28]. In addition, the SRMR is less than .1, which is generally considered favorable [35]. Lastly, the value of the RMSEA is less than .08, with the upper bound of its 90% confidence interval being less than .10, which is consistent with the hypothesis of reasonable overall model fit [9]. Given the overall favorable fit of the measurement model, we examined the reliability, convergent validity, and discriminant validity of the constructs.

To assess reliability, we computed Cronbach α for each construct. As can be seen in Table 2, Cronbach α for the constructs are all above the suggested minimum of .7 [13], with the exception of perceived amateurism (.667). As noted earlier, our unfavorable results for perceived amateurism mirror those found in the original scale development study by Fogg and colleagues [20]. Given this limitation, we conclude that the constructs in our study exhibit adequate reliability. Convergent validity was assessed through inspection of standardized factor loadings and average variance extracted (AVE). All factor loadings are statistically significant at $p < 0.01$. As shown in Table 2, the standardized factor loadings are above the suggested minimum of .7 [13], with the exception of two items in the perceived amateurism scale (.540 and .595). AVE for all constructs is larger than .5, the recommended minimum to establish convergent validity [27], again with the exception of perceived amateurism (.414). Given the limitations of perceived amateurism, we conclude that the measures exhibit adequate convergent validity. Lastly, we assessed discriminant validity by comparing the square root of AVE with the correlations between the constructs. As can be seen in Table 3, the square root of AVE is larger than any inter-construct correlation, which is an indicator of adequate discriminant validity [13], except for the correlation between purchase intention and perceived content

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

quality (r = .842). Although this result is not ideal, it has been suggested that inter-construct correlations of less than .85 indicate discriminant validity [8]. The fact that discriminant validity could not be established between the constructs of purchase intention and perceived content quality certainly limits the validity of our findings and points to a need for further research and scale refinement. Despite these shortcomings, we decided to accept the measurement model and proceed with the re-specification and analysis of the structural regression model.

Table 3: Inter-construct correlations*

Construct	**PI**	**DE**	**AM**	**CQ**	**HP**	**PP**
Purchase Intention (PI)	**0.799**					
Perceived Deceptiveness (DE)	-0.777	**0.842**				
Perceived Amateurism (AM)	-0.744	0.594	**0.643**			
Perceived Content Quality (CQ)	0.842	-0.831	-0.636	**0.841**		
Perceived Human Presence (HP)	0.574	-0.468	-0.401	0.589	**0.764**	
Perceived Physical Presence (PP)	0.611	-0.513	-0.410	0.530	0.453	**0.767**

* Square root of AVE shown in the diagonal

5.4 Structural Model

The analysis of the structural model depicted in Figure 2 converged to an admissible solution and values of selected indices suggest reasonably good overall model fit: X2(108) = 310.758, $p < .001$, CFI = .932, TLI = .914, NFI = .900, NNFI = .914, GFI = .992, AGFI = .988, SRMR = .067, and RMSEA = .077 with the 90% confidence interval .067 – .087. Although the chi-square statistic is significant, the ratio of chi-square to degrees of freedom is 2.878, below the suggested maximum of 3 [12]. All other fit indices are within the recommended guidelines, indicating overall good model fit [9], [28], [35]. Given the adequate model fit, we proceed with the analysis of individual paths in the structural model.

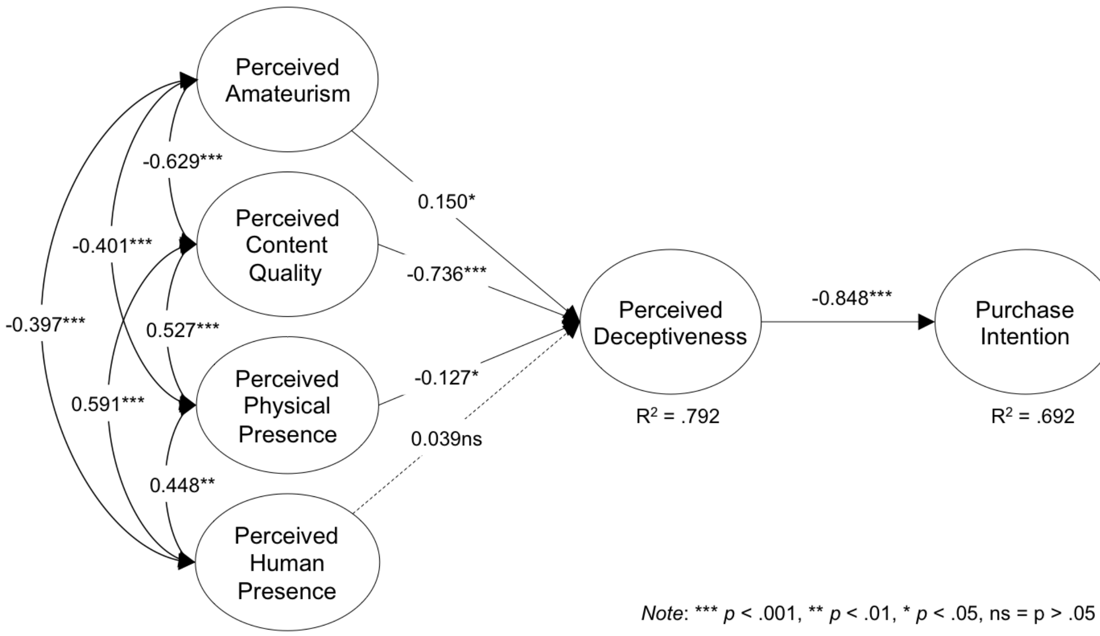

Figure 2: Results of structural model

As depicted in Figure 2, the path from perceived amateurism to perceived deceptiveness is positive and significant at $p < .05$, suggesting that an increase in perceived amateurism results in an increase in perceived deceptiveness. However, the standardized path coefficient of .150 indicates that the direct effect of perceived amateurism on perceived deceptiveness is relatively small. The path from perceived content quality to perceived deceptiveness is negative and significant at $p < .001$. This indicates that an increase in perceived content quality affects a decrease in perceived deceptiveness. Moreover, the standardized path coefficient of -.736 indicates that the direct effect of perceived content quality on perceived deceptiveness is relatively large. The path from perceived physical presence to perceived deceptiveness is negative and significant at $p < .05$. Thus, an increase in perceived physical presence leads to a decrease in perceived deceptiveness. However, the standardized path coefficient of -.127 indicates a relatively small direct effect of perceived physical presence on perceived deceptiveness. The path from perceived human presence to perceived deceptiveness is not significant at a conventional $p < .05$ level. This suggests that a

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

change in perceived human presence is not directly related to a change in perceived deceptiveness. Finally, the path from perceived deceptiveness to purchase intention is negative and significant at $p < .001$, indicating that an increase in perceived deceptiveness results in a decrease in purchase intention. Moreover, the standardized path coefficient of -.848 suggests that the direct effect of perceived deceptiveness on purchase intention is relatively large.

In addition, we tested a separate structural model, which includes product familiarity as a single-item antecedent to perceived deceptiveness. The purpose of this model was to test the possibility of product familiarity influencing the perception of deceptiveness. Given the theoretical discussion above, we expected product familiarity not to influence perceived deceptiveness. The structural model exhibited good fit: X2(120) = 321.286, $p < .001$, CFI = .933, TLI = .915, NFI = .898, NNFI = .915, GFI = .993, AGFI = .989, SRMR = .064, and RMSEA = .073 with the 90% confidence interval .063 – .082. The ratio of chi-square to degrees of freedom is 2.678, below the suggested maximum of 3, which along with the other fit indices suggests overall good model fit [9], [12], [28], [35]. In line with expectations, the path from product familiarity to perceived deceptiveness was not significant (standardized path coefficient of -.003, $p = .975$). Thus, the above findings relating to perceived deceptiveness are independent of differences in perceived product familiarity.

5.5 Post-Hoc Multi-Group Comparison

We conducted a multigroup comparison to test for potential differences between the three experimental groups. Following the recommendation in [35], we conducted several sequential model comparisons in order to test for differences between the groups. A model without any parameter constraints, called configural model [11], was specified, analyzed, and used as a basis for subsequent model comparisons. The configural model exhibits adequate overall model fit, as evaluated by its CFI and RMSEA value (see Table 4). Next, we tested for equality of factor loadings across groups. For this test, we specified a model that imposes equality constraints on the factor loadings between the three groups. A chi-square difference test between the first and second model indicates that the chi-square statistic did not change significantly ($p = .096$). Thus, we can conclude that the factor loadings between the groups are equal. Next, we tested for equality of item intercepts, while also keeping factor loadings equal. The chi-square difference test between the second and third model indicates that model fit changed significantly ($p < 0.001$). This suggests that item intercepts are different across groups. An inspection of the Lagrange Multipliers associated with model 3 suggests that the intercepts of four items are nonequivalent across groups. These items belong to the perceived physical presence factor (items PP2 and PP3) as well as the perceived amateurism factor (items AM5 and AM6). This is not surprising given that the experiment was specifically designed to elicit differences in perceived physical presence and perceived amateurism. Based on the fact that the differences in averages for these four items across groups is intentional, we created a model with partial measurement invariance (model 3a). A subsequent chi-square difference test between model 2 and model 3a suggests that the remaining item intercepts are not significantly different across groups ($p = .186$). Finally, we tested for equality of factor means, while also keeping loadings and intercepts equal – with the exception of items PP2, PP3, AM5, and AM6. The chi-square difference test between models 3a and 4 revealed a significant decrease in model fit ($p < .001$), thus indicating that the factor means are not equal across groups. The detailed results of the test for measurement invariance can be seen in Table 4.

Table 4: Test for measurement invariance

Model	**X^2**	***df***	**CFI**	**RMSEA**	**ΔX^2**	**Δ*df***	***p* for ΔX^2**
1. Configural	515.725	312	0.908	0.078			
2. Equal factor loadings	546.751	334	0.904	0.077	31.027	22	0.096
3. Equal factor loadings and intercepts	678.765	356	0.854	0.092	132.013	22	< 0.001
3a. Equal factor loadings and intercepts, with free intercepts for items PP2, PP3, AM5, AM6	565.204	348	0.902	0.077	18.453	14	0.186
4. Equal factor loadings, intercepts, and means with free intercepts for items PP2, PP3, AM5, AM6	965.953	360	0.727	0.126	400.749	12	< 0.001

An analysis of the parameter estimates of the factor mean differences between low quality (Group 3) and high quality (Group 1 and Group 2) conditions suggests that subjects in Group 3 perceived the website to be significantly more deceptive than subjects in Group 1 (Δ mean (M) = .898, standard error (SE) = .191, $p < .001$) and Group 2 (ΔM= 1.481, SE = .178, $p < .001$). Similarly, subjects in Group 3 exhibited a lower purchase intention than subjects in Group 1 (ΔM = -1.747, SE = .198, $p < .001$) and Group 2 (ΔM= -2.218, SE = .199, $p < .001$). In line with the treatment conditions, subjects in Group 3 perceived the website to have less content quality and less human presence than subjects in Group 1 ($\Delta M_{CQ} = -1.747$, $SE_{CQ} = .198$, $p < .001$, $\Delta M_{HP} = -.523$, $SE_{HP} = .187$, $p < .05$) and Group 2 ($\Delta M_{CQ} = -1.356$, $SE_{CQ} = .167$, $p < .001$, $\Delta M_{HP} = -.875$, $SE_{HP} = .203$, $p < .001$). In addition, there are significant differences in factor means between subjects in the two high quality conditions (i.e. Group 1 and Group 2). Specifically, subjects in the brick-and-mortar store condition (i.e. Group 2) perceived the website to be less amateurish, higher in physical presence, and of higher content quality than subjects in the online store condition (i.e.

Tamilla Mavlanova
Raquel Benbunan-Fich
Marios Koufaris
Guido Lang

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

Group 1) (ΔM_{AM} = -.402, SE_{AM} = .175, p < .001, ΔM_{PP} = 3.828, SE_{PP} = .168, p < .001, ΔM_{CQ} = .333, SE_{CQ} = .132, p < .05). Consequently, subjects in the brick-and-mortar condition (Group 2) indicated lower levels of perceived perceived deceptiveness and higher levels of purchase intention than subjects in the online store condition (Group 1) (ΔM_{DE} = -.584, SE_{DE} = .176, p < .001, ΔM_{PI} = .470, SE_{PI} = .151, p < .001).

6 Discussion

This study integrates signaling theory with deception and in doing so contributes to both fields. The results of the empirical study indicate that buyers interpret the signals presented through a website and discern the quality of the sellers. Previous studies had either studied signals as positive features [15] or deception resulting from the actions of a specific party [25]. By integrating both, this is one of the first studies that investigate how signals (positive and negative) displayed through a website ultimately contribute to form perceptions of deceptiveness, which is paramount for sellers who only present themselves online and buyers who transact with them.

There are several distinctive characteristics of this study. First, this research conceptualizes signals as aggregated groups instead of individual signals. Second, negative signals are considered in addition to positive signals. Third, the study focuses on the perceived deceptiveness of a website formed as the result of signal perception. Fourth, the use of three different websites ranging from low quality to high quality sheds light on how signal perceptions reflect the nature of each website.

Taken together, the results of this study enable us to answer the research question about the buyers' perceptions of positive and negative signals, their effect on perceived deceptiveness of a website, and purchase intentions during the pre-purchase phase of online shopping.

Our findings indicate that buyers assign more weight towards some signals (website content, physical presence and amateurism) and less weight towards other signals (human presence). These findings support tenets of signaling theory that underscore the importance of signaling costs. Signals are perceived by the amount of resources required to produce a signal. When signals are costly, buyers tend to believe that a seller is of high-quality otherwise the seller will incur costs in the form of forfeited wealth if the true quality of offerings is discovered [34].

Website content is an example of a costly signal as creating and updating the website content including company details, product images and product descriptions requires effort and constant monitoring of information quality. The same logic applies to the professionalism of a website. Keeping the website more professional and less amateurish requires resources that low quality sellers are not always willing or able to invest. Physical presence is a costly signal because it is prohibitively costly for a seller to provide false or incomplete information [52]. If the seller displays false physical address on the website, buyers can potentially verify this information. If the contact information is false, does not exist, or belongs to a different entity, buyers may perceive a seller as deceptive and the sale will not take place.

Negative signals were also found significant in our study. Although not deliberate, these signals form the perception of amateurism of a website, and have a positive effect on the perceived deceptiveness of a website. The contribution of this study is to examine negative signals and evaluate their role in the context of online commerce.

According to our results, unlike other signals, human presence signals do not seem to affect perceived deceptiveness. This phenomenon can be explained by the fact that the majority of our respondents were between 18-25 years old and are categorized as digital natives (e.g. persons born at the digital age as opposed to digital immigrants [45]. It is possible that for a new generation of online consumers human presence signals are less important as they grew up surrounded by online commerce and perceive e-commerce websites as purely digital.

Participants were able to perceive the three websites differently by evaluating aggregated signals. In fact, results of a post-hoc analysis demonstrate that there are significant differences in perceptions across websites (See Figure 3). The High Quality/Click and Mortar website is perceived as significantly superior to other two websites in terms of lack of amateurism, content quality, human and physical presence and purchase intentions. In addition, this website is perceived as the least deceptive out of all categories. There also differences between two online only websites. Overall, the High Quality/Online Only website is perceived as more professional, and less deceptive than the Low Quality/Online Only website.

These results show that users are able to see differences among websites of various quality and these differences are based on the availability of costly signals and a lack of negative signals. When there are more costly signals on the website and negative signals are absent, users perceive it as less deceptive and have more favorable purchase intentions.

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

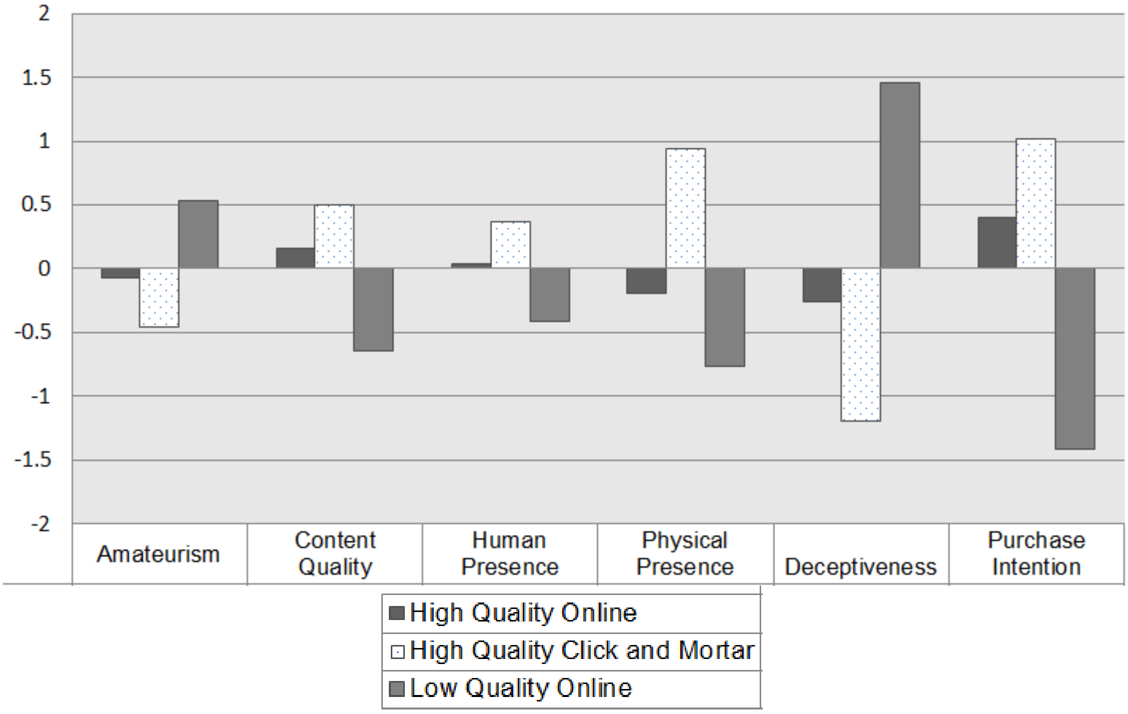

Figure 3: Differences among variables according to the subjects' perceptions

As hypothesized, perceived amateurism of a website and the quality of its content are found to be significant predictors of perceived deceptiveness albeit in opposite directions. While perceived amateurism increases the level of perceived deceptiveness, perceived content quality decreases the level of perceived deceptiveness. Thus, the implication for practitioners is to pay more attention to the quality and value of the information they provide and the way the information is presented on a website. This insight is important because to the best of our knowledge, no studies to date have reported the effect of signal perceptions on perceived deceptiveness in online commerce.

Figure 3 shows a comparison of signals perceptions by type of website and perceived deceptiveness and purchase intentions. In general, users are able to distinguish between click-and-mortar and online only websites, and, not surprisingly, have more favorable purchase intentions towards click-and-mortar websites. However, when comparing the two online-only websites, the differences are also significant. Users are able to distinguish quality differences between the two, and find the higher quality website less deceptive.

6.1 Theoretical Contributions

From the theoretical perspective, this study integrates a theory of deception with an economic theory of signaling. As such, it enriches the understanding of how economic theories can be informed and enhanced by other theories when applied to the context of e-commerce. With this theoretical background and different from existing literature that focused on isolated and positive signals, this study introduces positive and negative signals that are perceived collectively in an online shopping environment. The resulting research model is tested empirically.

In previous literature, signals were treated as present or absent [15]. This study provides a wider view of signals by evaluating perceptions of buyers dealing with signals presented in online environment. In addition, this study evaluates the role of signaling as a part of digital business strategy to reduce the perceived deceptiveness of a website. As the majority of retail websites are online only and do not have physical presence, it is important for sellers to signal quality and longevity to reduce perceived deceptiveness. As perceived deceptiveness is not well researched in the domain of online commerce, this study contributes to the literature on online deception.

6.2 Practical Contributions

Along with the increase in global e-commerce sales, e-commerce fraud is growing as well. Higher possibilities of online deception increase consumers' fears to shop online. Therefore, it is critical to understand what factors may alleviate potential concerns and produce more favorable purchase behavior intentions. This study fills the gap in this line of research by evaluating the effect of signals on perceived deceptiveness of a website.

The results of this study are useful for practitioners and can inform online retailers to focus their attention on signals that influence the buyers' perceptions of deceptiveness. Having demonstrated the role of signals in e-commerce, we

Tamilla Mavlanova
Raquel Benbunan-Fich
Marios Koufaris
Guido Lang

recommend that sellers who cannot establish physical presence, focus on content and design of their websites. More informative websites, that are easy to navigate and that offer a useful content may reduce the perceived deceptiveness of a website as high quality content and design may be perceived as costly signals that indicate longevity and high quality of an online seller.

In addition, website designers may find these findings valuable in their ongoing attempts to make websites more informative. We recommend designers to find ways to improve signal awareness and help online consumers understand signals. Consumers that notice and appreciate the signals have more valuable information for their decision making process.

6.3 Limitations

One limitation of this study is that only websites selling pharmaceutical products were used. This fact opens possibilities for future research seeking to evaluate the role of signals and signal perceptions across other industries. A second limitation is that research participants did not actually purchase the medicine. Should that be the case, potential buyers could be more concerned about the quality of websites. However, our results demonstrate that participants were able to clearly differentiate among websites of varying quality, which bodes well for their actual purchase behavior.

In addition, this study focuses only on pre-contractual issues in online retail and assesses the effect of signal perceptions before the transaction has taken place. This study paves the way for future studies that can investigate post-contractual issues.

This study also provides potential avenues for future research with additional constructs. Other signals worth exploring include perceptions of signals provided by third parties such as verification seals, consumer reviews and seller feedback. Further examination of signaling mechanisms can provide a richer explanation of antecedents of deception and trust in online storefronts, and enable the progress of online transactions in online retail. Lastly, we point to the need for further research on the constructs of purchase intention and perceived content quality. In this study we were unable to establish the discriminant validity of these constructs. Clearly, future research needs to address this shortcoming.

7 Conclusion

The results of this study show that the perceptions associated with specific website signals such as amateurism, content, and physical presence play a significant role in forming buyer's views of website deceptiveness. Unlike other studies that mostly examine positive signals, this research evaluates the effect of negative signals as well, and groups related signals in well-defined categories. With this approach, the study makes theoretical and practical contributions. At the theoretical level, the model and findings advance our understanding of how signaling and deception interact in online commerce. At a practical level, the results are informative for website designers, as well as potential buyers, regarding the importance of adequate signal presentation and evaluation in modern commercial websites.

References

[1] G. Akerlof, The market for lemons: quality uncertainty and the market mechanism, Quarterly Journal of Economics, vol. 84, no. 3, pp. 488-500, 1970.
[2] J. C. Anderson and D. W. Gerbing, Structural equation modeling in practice: A review and recommended two-step approach, Psychological Bulletin, vol. 103, pp. 411-423, 1988.
[3] J. Baker, D. Grewal and A. Parasuraman, The influence of store environment on quality inferences and store image, Journal of the Academy of Marketing Science, vol. 22, no. 4, pp. 328-340, 1994.
[4] R. Banker, I. Hwang and I. Wattal, Signaling mechanisms and survival of service providers in an electronic market, in the Proceedings of Americas Conference on Information Systems (AMCIS), paper 513, Lima, Peru, 2010, pp. 1-8.
[5] G. R. Bewsell, Distrust, fear and emotional learning: An online auction perspective, Journal of Theoretical and Applied Electronic Commerce Research, vol. 24, no. 2, pp. 1-12, 2012.
[6] D. Biswas and A. Biswas, The diagnostic role of signals in the context of perceived risks in online shopping: Do signals matter more on the web? Journal of Interactive Marketing vol. 18, no. 3, pp. 30-45, 2004.
[7] W. Boulding and A. Kirmani, A consumer-side experimental examination of signaling theory: do consumers perceive warranties as signals of quality? Journal of Consumer Research, vol. 20, no. 1, pp. 111-123, 1993.
[8] T. A. Brown, Confirmatory Factor Analysis for Applied Research. New York: Guilford Press, 2006.
[9] M. W. Browne and R. Cudeck, Alternative ways of assessing model fit, in Testing Structural Equation Models (K. A. Bollen and J. S. Long, Eds.). Newbury Park, CA: Sage, 1993, pp. 136-162.
[10] D. B. Buller and J. K. Burgoon, Interpersonal deception theory, Communication Theory, vol. 6, no. 3, pp. 203-242, 1996.

[11] B. M. Byrne, R. J. Shavelson and B. Muthén, Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement equivalence, Psychological Bulletin, vol. no. 105, pp. 456-466, 1989.
[12] E. G. Carmines and J. P. McIver, Analyzing models with unobserved variables: Analysis of covariance structures, in Social Measurement: Current Issues (G. W. Bohrnstedt and E. F. Borgatta, Eds.). Beverly Hills, CA: Sage, 1981, pp. 65-115.
[13] W. Chin, Commentary: Issues and opinion on structural equation modeling, MIS Quarterly, vol. 22, no. 1, pp. VII-XVI, 1998.
[14] W. Chu and W. Chu, Signaling quality by selling through a reputable retailer: An example of renting the reputation of another agent, Marketing Science, vol. 13, no. 2, pp. 177-189, 1994.
[15] B. L. Connelly, S. T. Certo, R. D. Ireland, and C. R. Reutzel, Signaling theory: A review and assessment, Journal of Management, vol. 37, no. 1, pp. 39-67, 2011.
[16] M. Darby and E. Karni, Free competition and the optimal amount of fraud, Journal of Law and Economics, vol. 16, no. 1, pp. 67-88, 1973.
[17] N. Dawar and P. Parker, Marketing universals: Consumers' use of brand name, price, physical appearance and retailer reputation as signals of product quality, Journal of Marketing, vol. 58, no. 2, pp. 81-95, 1994.
[18] P. Ekman, Telling Lies: Clues to Deceit in the Marketplace, Politics, and Marriage. New York: WW Norton and Company, 1992.
[19] T. Erdem and J. Swait, Brand equity as a signaling phenomenon, Journal of Consumer Psychology, vol. 7, no. 2, pp. 131-157, 1998.
[20] P. Everard and D. F. Galletta, How presentation flaws affect perceived site quality, trust, and intention to purchase from an online store, Journal of Management Information Systems, vol. 22, no. 3, pp. 56-95, 2005.
[21] J. Fogg, J. Marshall, O. Laraki, A. Osipovich, C. Varma, and N. Fang, What makes Web sites credible?: a report on a large quantitative study, in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems ACM New York, NY, USA, 2001, pp. 61-68.
[22] G. Gao, A. Gopal and R. Agarwal, Contingent effects of quality signaling: Evidence from the Indian offshore IT services industry, Management Science, vol. 56, no. 6, pp. 1012-1029, 2010.
[23] D. Gefen and D. Straub, Managing user trust in B2C e-Services, e-Service Journal, vol. 2, no. 2, pp. 7-24, 2003.
[24] D. Gefen, S. Wyss and Y. Lichtenstein, Business familiarity as risk mitigation in software development outsourcing contracts. MIS Quarterly, vol. 32, no. 3, pp. 531-542, 2008.
[25] S. Grazioli, Where did they go wrong? An analysis of the failure of knowledgeable internet consumers to detect deception over the internet, Group Decision and Negotiation, vol. 13, no. 2, pp. 149-172, 2004.
[26] D. G. Gregg and S. Walczak, Design your online auction business for success: An experiment comparing two eBay businesses, MIS Quarterly, vol. 32, no. 3, pp. 653-670, 2008.
[27] J. F. Hair, R. E. Anderson, R. L. Tatham, and W. C. Black, Multivariate Data Analysis. Fifth Edition. Englewood Cliffs, NJ: Prentice Hall, 1998.
[28] L. Hu and P. M. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, Structural Equation Modeling, vol. 6, no. 1, pp. 1-55, 1999.
[29] E. Huizingh, The content and design of web sites: an empirical study, Information and Management, vol. 37, no. 3, pp. 123-134, 2000.
[30] S. Jarvenpaa and N. Tractinsky, Consumer trust in an internet store: A cross-cultural validation, Journal of Computer-Mediated Communications, vol. 5, no. 2, pp. 1-35, 1999.
[31] P. E. Johnson, S. Grazioli, K. Jamal, and R. G. Berryman, Detecting deception: adversarial problem solving in a low base-rate world, Cognitive Science, vol. 25, no. 3, pp. 355-392, 2001.
[32] D. Kim and I. Benbasat, The effects of trust-assuring arguments on consumer trust in internet stores: Application of toulmin's model of argumentation, Information Systems Research, vol. 17, no. 3, pp. 286-300, 2006.
[33] D. Kim and I. Benbasat, Trust-Assuring Arguments in B2C E-Commerce: Impact of Content, Source, and Price on Trust. Journal of Management Information Systems, vol. 26, no. 3, pp. 175-206, 2009.
[34] A. Kirmani and A. R. Rao, No pain, no gain: A critical review of the literature on signaling unobservable product quality, The Journal of Marketing, vol. 64, no. 2, pp. 66-79, 2000.
[35] R. B. Kline, Principles and Practice of Structural Equation Modeling. Second Edition. New York: Guilford Press, 2005.
[36] N. K. Lankton and D. H. McKnight, What does it mean to trust facebook? Examining technology and interpersonal trust beliefs, The DATA BASE for Advances in Information Systems, vol. 42, no. 2, pp. 32-54, 2011.
[37] K. H. Lim and I. Benbasat, The effect of multimedia on perceived equivocality and perceived usefulness of information systems, MIS Quarterly, vol. 24, no. 3, pp. 449-471, 2000.
[38] T. Mavlanova and R. Benbunan-Fich, Counterfeit products on the internet: The role of seller level and product level information, International Journal of Electronic Commerce, vol. 15, no. 2, pp. 79-104, 2011.
[39] T. Mavlanova, R. Benbunan-Fich and M. Koufaris, Signaling theory and information asymmetry in online commerce. Information & Management, vol.49, no. 5, pp.240-247, 2012.
[40] T. Mavlanova, M. Koufaris and R. Benbunan-Fich, Website signal perceptions and seller quality identification, in the Proceedings of Americas Conference on Information Systems (AMCIS), Paper 147 Detroit, MI, 2011, pp.1-9.
[41] P. Milgrom and J. Roberts, Price and advertising signals of product quality, Journal of Political Economy, vol. 94, no. 4, pp. 796-821, 1986.

[42] D. P. Mishra, J. B. Heide and S. G. Cort, Information asymmetry and levels of agency relationships, Journal of Marketing Research, vol. 35, no. 3, pp. 277-295, 1998.
[43] P. A. Pavlou and M. Fygenson, Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior, MIS Quarterly, vol. 30, no. 1, pp. 115-143, 2006.
[44] P. A. Pavlou, H. Liang and Y. Xue, Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective, MIS Quarterly vol. 30, no. 1, pp. 105-136, 2007.
[45] M. Prensky, Digital natives, digital immigrants, On the Horizon, vol. 9, no. 5, pp. 1-6, 2001.
[46] R Development Core Team, R: a Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing, 2012.
[47] S. Ray, T. Ow and S. S. Kim, Security assurance: How online service providers can influence security control perceptions and gain trust, Decision Sciences, vol. 42, no. 2, pp. 391-412, 2011.
[48] I. Reay, S. Dick and J. Miller, An analysis of privacy signals on the world wide Web: Past, present and future, Information Sciences, vol. 179, no. 8, pp. 1102-1115, 2009.
[49] Y. Rosseel, lavaan: An R package for structural equation modeling, Journal of Statistical Software, vol. 48, no. 2, pp. 1-36, 2012.
[50] A. Schlosser, T. White and S. Lloyd, Converting web site visitors into buyers: How web site investment increases consumer trusting beliefs and online purchase intentions, Journal of Marketing, vol. 70, no. 2, pp. 133-148, 2006.
[51] J. Song and M. Zahedi, Web design in e-commerce: A belief reinforcement model, Management Science, vol. 51, no. 8, pp. 1219-1235, 2005.
[52] M. Spence, Job market signaling, The Quarterly Journal of Economics, vol. 87, no. 3, pp. 355-374, 1973.
[53] R. E. Turner, C. Edgley and G. Olmstead, Information control in conversations: Honesty is not always the best policy, Kansas Journal of Sociology, vol. 11, no. 1, pp. 69-89, 1975.
[54] S. Utz, U. Matzat and C. Snijders, On-line reputation systems: The effects of feedback comments and reactions on building and rebuilding trust in on-line auctions, International Journal of Electronic Commerce, vol. 13, no. 3, pp. 95-118, 2009.
[55] S. Wang, S. E. Beatty and W. Foxx, Signaling the trustworthiness of small online retailers, Journal of Interactive Marketing, vol. 18, no. 1, pp. 53-69, 2004.
[56] D. Wells, J. S. Valacich and T. J. Hess, What signals are you sending? How website quality influences perceptions of product quality and purchase intentions, MIS Quarterly, vol. 35, no. 2, pp. 373-396, 2011.
[57] B. Xiao and I. Benbasat, Product-related deception in e-commerce: A theoretical perspective, MIS Quarterly, vol. 35, no. 1, pp. 169-195, 2011.
[58] R. W. Zmud, T. Shaft, W. Zheng and H. Croes, Systematic differences in firm's information technology signaling: Implications for research design, Journal of the Association for Information Systems, vol. 11, no. 3, pp. 149-181, 2010.

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 10 / ISSUE 1 / JANUARY 2015 / 19-34

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762015000100003

Appendix A: The Description of the Coding Protocol

	Definition	References	Coding Rules*
Amateurism	Deficient, incomplete or sloppy presentation of the website.	[16], [21]	Presence of broken links, typographical errors, unexpected unavailability, links to bogus websites and mismatching between domain and company name.
Content	Presence of relevant information provided on the website	[26], [29], [57]	Availability of customer reviews, shopping advice, articles about medicines, and product information and the availability of website policies (e.g. privacy policy etc.).
Human Presence	Evidence of real employees working behind the website	[21], [36]	Presence of human pictures, live chat and social signals (Facebook, Twitter).
Physical Presence	Indicators that the seller also conducts business in physical locations or stores.	[21], [32]	Presence of physical address, store locator, phone and email information.

* For more details about the coding rules, please see [39]