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PROVIDER- VS. USER-GENERATED RECOMMENDATIONS ON E-COMMERCE WEBSITES – COMPARING COGNITIVE, AFFECTIVE AND RELATIONAL EFFECTS

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Completed Research Paper

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Abstract

With the proliferation of recommendation functions (RF) on e-Commerce websites, there is growing confusion about how various RF types affect consumers' beliefs and behavior. Despite the importance of understanding the differential effects of RF types, research focusing on the comparison between provider-generated recommendations (PGRs) and user-generated recommendations (UGRs) has received little attention. This paper reports on two empirical studies that examine the differential effects of PGRs and UGRs on cognitive, affective and relational aspects of consumer beliefs and show how these perceptions influence RF usage intentions. The findings from a field survey (N=366) and a laboratory experiment (N=161) indicate that UGRs (such as consumer reviews) have stronger impact on users' trusting beliefs and perceived affective quality (i.e. on relational and affective perceptions respectively) than PGRs*. Conversely, PGRs (such as collaborative filtering-based RFs) are superior to UGRs in affecting perceived usefulness (i.e. cognitive perceptions). Further, trusting beliefs and perceived affective quality were found to be stronger predictors of usage intentions than perceived usefulness in UGR rather than PGR contexts. By showing which RF types influence different consumer perceptions, the study provides practitioners with clear guidelines on how to design sales efficient e-Commerce websites while enhancing online-consumers' overall shopping experience.*

Keywords: Online recommendations, provider-/user-generated content, e-Commerce, technology acceptance, perceived usefulness, trusting beliefs, perceived affective quality

Introduction

Contrary to offline retail channels, e-Commerce consumers are not able to try out products before making purchases, which may significantly increase their level of uncertainty regarding product quality, and thus hinder their purchasing decisions. To compensate for the lack of quality inspections in online markets, many e-Commerce vendors provide system-filtered recommendations (i.e. provider-generated recommendations) that recommend products to consumers based on their past buying behavior or on the preferences of other like-minded consumers. Another way to provide recommendations is to allow consumers to write reviews about the quality of products or to share their experiences in discussion forums or blogs (i.e. user-generated recommendations). Due to their high degree of acceptance among consumers, different types of IT-enabled provider-generated recommendations (PGRs) and user-generated recommendations (UGRs) – that are defined in this paper as specific instances of online recommendation functions (RFs) – are becoming increasingly available on websites to provide customers with shopping assistance, improve their decision quality, and help buyers and sellers reduce information overload (Park and Lee 2008). It is estimated that at least 43% of e-Commerce websites already offer customer reviews and ratings (Gogoi 2007). However, though the number of different forms of recommendation functions has exploded in recent times[1], there is still confusion about their effectiveness and about the differential effects (i.e. cognitive, affective or relational effects) they have on users' beliefs and behavior. Are consumers more responsive to recommendations generated by the website provider through sophisticated agent technology or are they more inclined to follow recommendations generated by other consumers ("human agents")? More specifically, which of the two RF types (i.e. PGRs and UGRs) is superior in evoking consumers' cognitive, affective and relational beliefs and ultimately affecting their usage intentions?

The present study extends previous research related to the effect of recommendation functions on consumer behavior by distinguishing between provider- and user-generated recommendations. It empirically investigates recommendation source effects in an extended technology acceptance model (TAM) including cognitive, affective and relational dimensions of consumer beliefs. As such, this study reveals the differential effects of different RF types by examining their influence on perceived usefulness (i.e. cognitive dimension), perceived affective quality (i.e. affective dimension) and trusting beliefs (i.e. relational dimension). The study has two major objectives: (1) investigating how provider- and user-generated recommendations compare with respect to their impact on users' perceived usefulness, trusting beliefs and affective quality of a recommendation function, and (2) examining how cognitive, affective and relational beliefs affect users' intentions to use the recommendation function as a decision aid.

This research makes potentially useful contributions to research and practice. First, it extends existing literature related to e-Commerce product recommendation (e.g. Kumar and Benbasat 2006) and electronic word-of-mouth (eWOM) (e.g. Park et al. 2007). While the effects of cognitions and emotions (e.g. perceived enjoyment or satisfaction) (e.g. Parboteeah et al. 2009) as well as of cognitions and relational aspects (e.g. Qiu and Benbasat 2009) have been explored independently in the Internet and e-Commerce product recommendation literature, there is no clear understanding of which RF types more strongly affect consumers' cognitive, affective or relational beliefs. In addition, it is not clear which consumer beliefs (i.e. cognitive, affective or relational) are stronger in influencing RF usage intentions. Second, by examining how different RFs affect perceived usefulness, trusting beliefs and perceived affective quality, this study provides practitioners with clear guidelines to design sales efficient e-Commerce websites susceptible to enhance online-consumers' overall shopping experience. Finally, the study's results are based on data collected from two successive studies: an online-survey (N=366) and a controlled laboratory experiment (N=161), thus providing a clearer and more robust understanding of the impact of PGRs and UGRs on cognitive, affective and relational aspects of consumer beliefs and intentions.

[1] For example, Amazon currently offers more than 18 different instances of RFs ranging from "Recommended For You" to "Customers Who Bought This Item Also Bought" for PGRs and online-reviews or customer blogs for UGRs (Hansen et al. 2007).

Background and Hypotheses Development

Background and Literature Review

As shown in Table 1, this study distinguishes between two different types of RFs on e-Commerce websites (i.e. PGRs and UGRs).

Table 1. Main distinguishing characteristics of PGRs and UGRs on e-Commerce websites

Characteristic	**Provider-generated recommendations (PGRs) (e.g. collaborative filtering)**	**User-generated recommendations (UGRs) (e.g. online reviews)**
Author/Creator of content	**Provider**	**Other consumers/users**
Originality of content	**System-filtered** content extracted from statistical analyses	Original, first-hand content
Source of recommendation preferences	Attribute-based preferences based on past consumer **behavior and profiles**	Preferences based on past consumer **experience and/or opinions**
Number of data points included in the recommendation	Many	Few
Media richness of recommendations	Text, pictures (, multi-media)	(Predominantly) text-based
Level of e-Commerce provider's control over content layout	High	Low

PGRs (also called product recommendation agents) are Internet-based software that carry out a set of operations on behalf of users and provide shopping advice based on users' needs, preferences, profiles, and previous shopping activities (Maes et al. 1999). They have been proposed as support tools for consumers at various stages of their decision-making process. Different types of PGRs have been developed and are currently used within e-Commerce websites. Content-based and collaborative-filtering-based recommendations are the most widely used classes of RFs (Wei et al. 2005). Content-based filtering recommendations are typically based on a set of algorithms that derive recommendations for a particular user from that user's profile or from knowledge about that user's past behavior (Ansari et al. 2000). A user profile is based on explicit interests and on past behavior of the user. For example, a content-based filtering system would recommend a book to a user based on the user's expressed interests about books in his/her profile or based on the user's previous book purchase history. Alternatively, collaborative-filtering recommendations mimic "word-of-mouth" recommendations and use the buying behavior of like-minded people to generate recommendations (Ariely et al. 2004). Recommendations are commonly extracted from statistical analysis of patterns and analogies of data drawn from evaluations of items (ratings) given by other users or implicitly by monitoring the behavior of other users in the system (Montaner et al. 2003). For example, a collaborative filtering-based RF would recommend a book to a user because other users who have similar interests rated the book highly.

On the other hand, recommendations that are based on user-generated content such as consumer reviews, discussion forums or blogs are not based on system-filtered content but rather on original content, where a software system does not interfere with the recommendation generation process. UGRs on e-Commerce websites are thus not generated by information technologies; instead, they are *mediated by them*. Furthermore, UGRs draw their data points from usage experiences and opinions that are directly reported by other consumers (Cheong and Morrison 2008), whereas PGRs automatically and statistically process past buying behaviors or interest profiles. Additionally, since UGRs cannot be presented in a standardized and consistent layout across consumers, website providers have less control over the presentation structure of UGRs as they do over PGRs. While the large majority of consumer reviews on major e-Commerce platforms (such as Amazon.com or Zappos.com) are based on text and appear with different text length and numbers of paragraphs, PGRs are always presented in a consistent layout as designed by the website provider including text, pictures and multimedia files (i.e. audio and/or video). Finally, UGRs are based on single data points (e.g. experiences, opinions) from one or few consumers, whereas PGRs statistically aggregate and evaluate many data points related to consumers.

Exploring the effects of recommendation functions on individual product choice is not a new field of research. Building on traditional word-of-mouth (WOM) literature (e.g. Brown and Reingen 1987; Herr et al. 1991; Katz and

Lazarsfeld 1955) and motivated by the increasing importance of the Internet as major sales channel, researchers have conceptually and empirically studied the effects of human and software recommendation agents on e-Commerce websites (e.g. Xiao and Benbasat 2007). Though a large number of studies have investigated the effects of recommendation functions on different outcome criteria such as *customer satisfaction* (Jiang et al. 2010), *decision quality* (Häubl and Trifts 2000), *consumer trust* (Wang and Benbasat 2005; Komiak and Benbasat 2006), *the propensity to follow* (Senecal and Nantel 2004), and *financial performance* (Jiang and Wang 2008), studies comparing the differential effects of distinct RF types are still relatively scarce. While some researchers studied the effects of different *levels of personalization* of recommendation functions (Komiak and Benbasat 2006), their *quality* (e.g. good vs. bad recommendations; Häubl and Trifts 2000), *human appeal* (e.g. Cyr et al. 2009; Qiu and Benbasat 2009) and *persuasiveness* (Duan et al. 2008), little empirical evidence exists regarding how people's perceptions, affections and cognitions are comparatively influenced by RF types.

To the knowledge of the authors, there is only the study of Kumar and Benbasat (2006) that empirically analyzed the direct effects of provider recommendations and consumer reviews on perceived usefulness (i.e. cognitive aspect) and social presence (i.e. social/relational aspect) of an e-Commerce website. However, despite the call for more research on the effect of recommendation agents on different types of users' evaluations of RFs (Xiao and Benbasat 2007) and the crucial role that affective/emotional and social/relational factors play in technology acceptance phenomena (Bagozzi 2007), there is still paucity of empirical research that comprehensively compares cognitive, affective, and relational effects of PGRs and UGRs on e-Commerce websites. Addressing this research gap thus may inform researchers on a relevant topic in human-computer interaction, and also provide e-Commerce vendors with recommendations regarding usage of different RFs at different stages of consumers' buying processes.

Research Model and Hypotheses Development

To illustrate how PGRs and UGRs compare in their relational, cognitive and affective effects and how they influence perceived usefulness, trusting beliefs, perceived affective quality, and intention to use, we propose the research model shown in Figure 1.

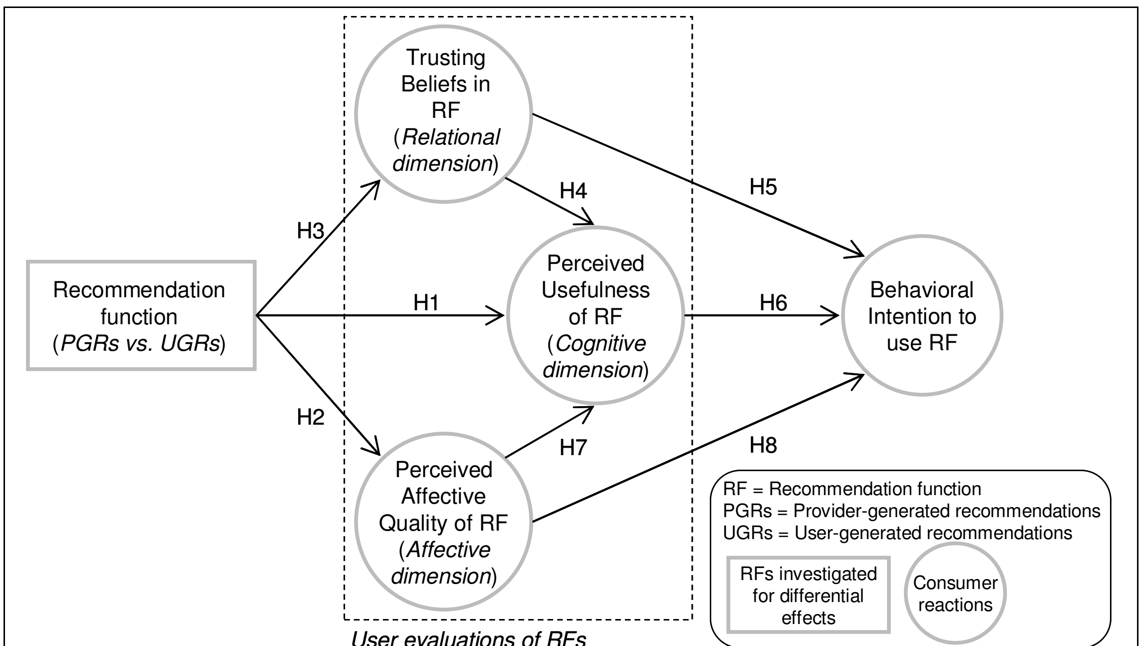


Figure 1. Proposed Conceptual Model and Research Hypotheses

The relational, cognitive and affective dimensions we examine in our conceptual model are based on the classification of user evaluations of RFs by Xiao and Benbasat (2007). As RFs are basically used to support decision-making in online environments, users' intentions to use them can be partly explained by traditional models of IS adoption (e.g. the technology acceptance model (TAM) (Davis et al. 1989)). However, cognitive beliefs, such as perceived usefulness in TAM, fail to capture other relevant reactions (e.g. relational and affective reactions) that IT artifacts in general and RFs in particular elicit in consumers. Several authors have advised to include factors that complement existing knowledge of technology acceptance (e.g. Bagozzi 2007).

In this research, our goal is to study how PGRs and UGRs differ in eliciting cognitive, but also affective and trusting beliefs that may in turn influence usage intentions. Perceived affective quality is part of our conceptual model because it captures a person's primitive and multi-faceted affective reactions to RFs in contrast to perceived enjoyment or satisfaction which can also be considered as affective reactions to IT but which are situated at a secondary or higher level than perceived affective quality. Integrating perceived affective quality in our conceptual model thus allows us to gain a more foundational understanding of affective consumer reactions (Zhang and Li 2005). We include trusting beliefs in our study because it is usually difficult for users to determine whether (human and software-based) RFs are capable of product screening and evaluation and whether RFs act solely in the interest of the users or for the online store where they reside (Xiao and Benbasat 2007). In a focus group experiment, Andersen et al. (2001) also found that trust in RFs is the most important expectation users have which represents a crucial relational aspect in a consumer's interaction with an RF. As such, users' trusting beliefs encompass important social and relational aspects that ought to be considered when comparing different kinds of user evaluations. When referring to trusting beliefs in RFs in the following sections, and similar to Wang and Benbasat (2005), we will consistently link consumers' trusting beliefs to *relational* effects in order to emphasize the importance of trust-building in the relationship between consumers and RFs.

To conceptualize the differential effects of PGRs and UGRs, we first draw on literature from various disciplines including consumer, communication, trust and information processing research. We then briefly reexamine previous literature in the context of TAM to conceptualize the paths influencing behavioral intentions to use RFs.

PGRs, UGRs and differential cognitive, affective and relational effects

In the context of e-Commerce online recommendations, empirical research indicates that RFs help consumers manage the overwhelming amount of information and choices available in electronic shopping environments by guiding them to a set of relevant products that are likely to fit their needs (Häubl and Trifts 2000; Senecal and Nantel 2004). This enables consumers to cope with information overload by reducing their search costs. It also enhances consumers' effectiveness in finding suitable products and making satisfying buying decisions (Hanani et al. 2001; Komiak and Benbasat 2006). Online product RFs are also perceived as being more than just technologies or tools. They are virtual decision aids that help execute more effective decision-making. The theory of human information processing (Simon 1955) argues that, because of limitations in their cognitive capacity that include limited working memory and limited computational capabilities, people tend to 'satisfice' in processing information and making decisions. This theory also posits that consumers reduce their cognitive burden in making decisions by adopting a two-stage decision-making process. In the first stage, the set of products (alternatives) is reduced to a manageable level, while the second stage involves a detailed and in-depth evaluation of the products in the reduced set. Usage of RFs lowers search costs for the consumers by helping them reduce the size of the set of alternatives and better evaluate product items that are on a consumer's shortlist.

Generally, both PGRs and UGRs were found to significantly affect perceived usefulness (PU) due to their capability to reduce the cognitive process of sifting through multiple alternatives and better evaluate product items (e.g. Häubl and Trifts 2000; Kumar and Benbasat 2006). However, although the impact of PGRs and UGRs on PU has been examined in previous empirical studies, the effects of both types of RFs on PU have not been explicitly compared. In this study, we argue that PGRs are more effective in reducing search costs for consumers and thus have a stronger impact on PU than UGRs. PGRs usually provide more task-related cues and more comprehensive information for the evaluation of several products than UGRs can provide. In this regard, Parboteeah et al. (2009) found that task-relevant cues (i.e. all cues that enhance the utilitarian value) of a website have a stronger impact on PU than mood-relevant cues (i.e. cues that create an atmosphere that has the potential to make the shopping experience more pleasurable).

In the context of our study, we argue that by having more task-relevant cues, PGRs facilitate and enable the consumer's shopping goal attainment better than UGRs (Eroglu et al. 2001). PGRs provide effective navigation aids and a consistent interface design on which all product-related information (including pictures) of recommended alternatives is presented which enables users to quickly screen out unsuitable products or select suitable products thus facilitating a consumer's shopping task. In contrast, UGRs include in the majority of cases only textual comments that do not have a consistent interface design across different UGRs; neither do they contain pictures that would make key product information more accessible (Biehal and Chakravarti 1983; Childers 1986). Empirical studies in educational psychology (i.e. reading comprehension) research found that the cognitive effort for reading full-text sentences and passages is higher compared to screening pictures and small chunks of key product information (Britton et al. 1982). As UGRs such as consumer reviews consist of wordy text comments that differ in length and writing style, consumers have to first sift through this unstructured text to get to relevant product information that help them in their shopping task. Taken together, these arguments lead to the proposition that PGRs are perceived as more useful in filtering alternatives and supporting the shopping task than UGRs[2], hence:

H1: *Consumers will perceive greater PU of RFs with PGRs than of those with UGRs.*

IT artifacts have been found to generate cognitive, and also affective arousal in IT users, thus showing both hedonic and utilitarian value of IS (e.g. van der Heijden 2004). Drawing on consumer research and retailing literature (e.g. Holbrook and Hirschman 1982), studies related to Internet shopping and e-Commerce recommendation functions have constantly shown that various website characteristics enhanced users' perceptions of hedonic value, examples of such characteristics are: socially rich text contents and personalized greetings (Gefen and Straub 2002), emotive text and pictures of humans (Hassanein and Head 2005), and functionalities such as live chat and online reviews (Cyr et al. 2007). More generally, the effects of hedonic beliefs have also been identified as important determinants of online customer loyalty (e.g. Koufaris 2002) and have been found to play at least an equal role as instrumental beliefs (Childers et al. 2001). Though some studies have investigated the affective impact of RFs in e-Commerce by differentiating between specific RF characteristics (such as anthropomorphic elements (Qiu and Benbasat 2009)), there is, to the best of our knowledge, no study that has explored the differential effects of PGRs and UGRs that could be applied to strengthen the hedonic value of RFs.

In this study, perceived affective quality (PAQ) is used to capture the hedonic value of consumer's interaction with RFs. According to Zhang and Li (2004), PAQ refers to an individual's perception of an object's ability to change his or her core affect which is a state that is consciously accessible as a simple, non-reflective feeling that is an integral blend of hedonic or valence value (pleasure–displeasure, the extent to which one is generally feeling good or bad) and arousal or activation value (sleepy–activated, the extent to which one is feeling engaged or energized). Core affect is considered to be free of any implied cognitive structures and the core of all emotion-laden events (Russell 2003). The concept of core affect is similar to what some psychologists call primary emotions (Brave and Nass 2003). PAQ in the context of IS research is about a person's primitive affective reaction to an IT. The emphasis on perception of affective quality as a primitive affective reaction to IT differs from other studies that may consider some affective or emotional aspects such as computer anxiety, perceived enjoyment, and satisfaction, which can all be considered affective reactions to IT but are at a secondary or higher level than PAQ (Zhang and Li 2005).

Applying this concept to our research setting, we argue that UGRs are likely to produce higher PAQ than PGRs. The stories and narratives of personal experiences including specific examples make up the bulk of what a reader will find in UGRs (Cheong and Morrison 2008). As Deighton et al. (1989) pointed out, stories have an ability to draw in and cause the reader to empathize with the feelings of the writer, in effect, creating vicarious experience. Moreover, communication research has shown that vivid, concrete examples have strong impact on users' beliefs and affections (Tal-Or et al. 2004; Reinard 1988). In particular, some studies in persuasion and reading research found that narrative messages are more concrete, persuasive and emotional than statistical information (e.g. O'Keefe 2002; Sadoski et al. 1988). Without examples, ideas often seem vague, impersonal, and unemotional. With examples, ideas become specific, personal, and vivid producing arousing feelings (Sherman et al. 1999). While UGRs convey first-hand experiences, evaluations and opinions of single or few consumers, PGRs present more abstract and impersonal information, as such information is based on statistical evaluations of a massive amount of preference data.

Based on these differing mood-relevant cues, it can be argued that UGRs are more likely to stimulate emotional responses than PGRs (Parboteeah et al. 2009; Cheong and Morrison 2008). Similarly, given that UGRs often comprise elements of stories (e.g. plot, characters, drama), UGRs may have a greater ability to generate empathy among users and thus to affect consumers via direct emotional "contagion" (Cheung et al. 2009). In this regard, enthusiasm expressed in UGRs describing the joys of a particular product could for example directly generate some similar feelings in the minds of the readers (Bickart and Schindler 2001). Due to the oftentimes emotive text quality

[2] Similar to Qiu and Benbasat (2009), the effect of perceived ease of use (PEOU) on behavioral intentions was not examined in this research not only because it has been investigated in numerous TAM-related studies but also due to the focus of this paper. We do not intend to reexamine the interrelationships between all TAM-related constructs; instead, we only focus on those constructs that were consistently shown to affect usage intentions across different IS types.

of UGRs, consumers can thus become emotionally "immersed" in the e-Commerce website (Hassanein and Head 2005). By contrast, on most e-Commerce websites, PGRs deliver statistical data (e.g. "51% that viewed this item also bought it" etc.) in conjunction with key product information (e.g. price, key features) that is clearly arranged and easy to perceive. However, PGRs neither present the product information in a coherent (personal) story nor do they use emotive text or specific examples, suggesting that PGRs evoke less PAQ in consumers than UGRs. We therefore hypothesize that

H2: *Consumers will perceive greater PAQ of RFs with UGRs than of those with PGRs.*

In a growing body of IS research, trust has been integrated as an important antecedent to technology acceptance (e.g. McKnight et al. 2002a; Cugelman et al. 2009). More specifically, empirical studies of trusting beliefs in an e-Commerce vendor and in RFs reveal that trust plays an important role in indirectly (e.g. via PU, PEOU or perceived risk) and/or directly affecting consumers' usage intentions (Pavlou 2003; Qiu and Benbasat 2009). Trust in a RF is considered an extension of interpersonal trust in technological artifacts and can be considered a central characteristic of *relationships* between different parties that promotes effective knowledge sharing and creation (Wang and Benbasat 2007). When consumers form their initial trusting beliefs (TB) in a RF, the perceived quality of the information provided by the recommendation function contributes to the evaluation of the RF's trustworthiness. Users make inferences about the RF's trustworthiness by reflecting on issues such as the amount and scope of explanatory information it provided, or how well the recommended products conform to the preference structure users have specified. Users' TB in RFs can be enhanced when RFs provide additional information in the form of explanations (e.g. how, why and trade-off explanations) to reveal their underlying reasoning process and justify their recommendations (Wang and Benbasat 2007).

These findings can be extended to the differential effects of UGRs and PGRs on trusting beliefs. We argue that UGRs are more likely to evoke TB in RFs than PGRs. UGRs on e-Commerce websites typically include first-hand experiences and explanations of other users that report on how and why they have (or not) bought the product thereby unfolding their reasoning process. Moreover, UGRs let users learn about the reasoning process of other users from which they can infer whether the product is suitable or not. Irrespective of the relevance or irrelevance of the product recommendation for them, users can follow the argument on which another user made his or her decision. This transparency of the reasoning process is a key characteristic of UGRs and may contribute to building up user trust (Abrams et al. 2003). By contrast, the majority of PGRs typically lack adequate explanation facilities (Wang and Benbasat 2007). They provide an explanation for suggesting a product only in the sense that they present concrete product alternatives based on a user's or other users' preferences or past behavior. However, they typically lack information and concrete explanations on how the product can be used or why a product might be suitable. This prevents PGRs from revealing the underlying reasoning process that govern an RF's decision making and thus from demonstrating the competence, benevolence and integrity that enable the RF to generate recommendations. Empirical studies in the e-Commerce product recommendation literature also found that this kind of information asymmetry (i.e. that a RF possesses more information than the user with respect to the underlying logic of the RF's recommendation) hamper consumer trust toward the RF (e.g. Wang and Benbasat 2007).

In addition to product-related information and explanations, other sources are also used by consumers to form their trusting beliefs in RFs, especially by those who have limited product knowledge and therefore cannot accurately appraise the completeness and integrity of the information provided by the RF. When people interact with others for the first time, the initial phase of trust building is based on "whatever information is available" (Meyerson et al. 1996). Signaling theory argues that when facing such difficult decisions about quality, individuals attend to particular kinds of informational cues (Kirmani and Rao 2000): they look for indicators or correlates of quality that are difficult to fake such as the trustee's physical appearance, the online vendor's guarantee policies, or the recommendation source (e.g. Pennington et al. 2003). As we compare PGRs and UGRs on their differential effects on trusting beliefs in our study, reflecting on the source credibility (i.e. the credibility a RF conveys with the presented recommendation) may have particular explanatory value in this context. Research on communication source effects has a long tradition in communication, consumer and marketing research. Hovland and Weiss (1951) for example showed that the communicator's credibility, attractiveness, physical appearance, familiarity, and power, all of which are attributes of the information source, can have an impact on the credibility of the message (Hovland and Weiss 1951).

Past studies also indicate that source credibility determines the effectiveness of a communication in the off-line world and that audience's attributions of a source's intentions are a key factor in the perception of trustworthiness (Eagley et al. 1978). People tend to believe information from a highly credible source and more readily accept the information. Conversely, if the source has low credibility, the receiver is less likely to accept that information (Smith et al. 2005). The effect of source credibility is believed to also apply in the on-line environment. Wathen and Burkell's (2002) research found for example that web information receivers considered virtual source credibility as an important indicator of information credibility. The recommendation source may especially be relevant when comparing PGRs and UGRs. By definition, UGRs include other users' opinions and accounts of personal product experiences and are likely to be judged to emanate from trustworthy sources because their authors are fellow consumers who may share similar interests and may have used the product in a real-world setting. Conversely, as PGRs are produced by the e-Commerce vendor, they are more likely to be perceived to have a vested interest in promoting the product to increase sales (Cheong and Morrison 2008), which in turn may decrease consumers' trusting beliefs in the recommendation. Furthermore, PGRs may be attributed intentions to manipulate the reader in the sense that only one-sided (positive) recommendations are presented (Jaspars et al. 1983). By contrast, (both one or a collection of) UGRs may include two-sided messages and thus present more complete information which are likely to be perceived as more credible (Cheung et al. 2009; Wathen and Burkell 2002). As such, we propose that

H3: *Consumers will have higher TB in RFs with UGRs than in those with PGRs.*

Antecedents of RF usage intentions

The connections between trust and TAM have been widely discussed in previous studies (e.g. Pavlou 2003; Gefen et al. 2003; Wang and Benbasat 2005). Gefen et al. (2003) added consumer trust to the traditional TAM model in the context of online shopping, arguing that trust, conceptualized as a set of trusting beliefs toward an online vendor, would directly affect intentions to use a B2C website, along with PU. Trust in a merchant can also affect PU in both the short and long terms. Wang and Benbasat (2005) extended this integrated trust-TAM model to the context of online recommendation agents and found that initial trust in online recommendation agents affects usage intentions as well as consumers' PU of the agent. Follow-up studies in e-Commerce product recommendation research (e.g. Qiu and Benbasat 2009) confirmed the relationships between TB, PU and behavioral intentions (BI). Thus, for replication purposes, these relationships are hypothesized in this study:

H4: *Users' TB in a RF will positively affect PU of the RF.*

H5: *Users' TB in a RF will have a positive effect on behavioral intentions to use the RF.*

H6: *Users' PU of a RF will have a positive effect on behavioral intentions to use the RF.*

Zhang et al. (2006) suggest that PAQ of a technology is an important dimension of technology acceptance and usage. Based on Russell's emotional episode (Russell 2003), they empirically investigated PAQ's influence on TAM variables and found that users' primitive affective reactions (i.e. PAQ) toward an IS have an impact on their consequent reactions such as PU and behavioral intentions. PAQ's impact on PU is based on the notion that "feeling pleasant and being intrigued by the technology, the person would positively estimate the potential consequences of using the technology toward her goals according to the principle of mood congruence" (Zhang and Sun 2006, p. 4; see also Bagozzi et al. 1993). Lending support to PAQ's impact on PU, Venkatesh et al. (2002) also hypothesized and found that intrinsic motivation increases the deliberation and thoroughness of cognitive processing and leads to enhanced perceptions of extrinsic motivation conceptualized as perceived usefulness (Venkatesh et al. 2002). Several empirical studies could also find a significant direct relationship between PAQ and behavioral intentions to use a system (e.g. Zhang and Li 2004; Sanchez-Franco 2010). Applying the PAQ concept to e-Commerce product recommendation research, we argue that PAQ of RFs affects usage intentions indirectly via the stimulation of users' cognitive processing (i.e. PU) thus enhancing their capacities to pursue their shopping goal. Further, a user's PAQ of RFs is also likely to affect usage intentions directly. When a RF evokes arousing and pleasant feelings in users, users are likely to be more engaged in using the RF and are more likely to continue to use it in the future. Conversely, when RFs are perceived as drowsy or displeasing, users will refrain from using the RF again. Taken together, we reexamine the relationships between PAQ, PU and BI in the context of e-Commerce product RFs and propose that

H7: *Users' PAQ of a RF will positively affect PU of the RF.*

H8: *Users' PAQ of a RF will have a positive effect on behavioral intentions to use the RF.*

Research Method

To test the research model depicted in Figure 1, we designed and conducted two studies. The first study was based on an online-survey (N=366) and the second study was based on a controlled laboratory experiment (N=161). Digital cameras were chosen as the target product in both studies due to the high number of their product attributes (e.g. zoom and resolution), the large number of alternative models available on the market, and the short life span of each generation of products. These characteristics require a certain level of expertise from consumers making the use of RFs more relevant on e-Commerce websites (Qiu and Benbasat 2009).

Study 1: Online-survey

Amazon was chosen as the study context because it is recognized as one of the leading e-Commerce retailers and is a positive example for other online stores in terms of the way it implements support for the provision of PGRs and UGRs. Similar to previous online-recommendation studies (e.g. Kumar and Benbasat 2006), we developed a Java-based software agent (called "AmaFilter") for the Amazon web services environment that intercepted the web pages sent by Amazon and filtered the content to randomly generate PGRs and UGRs in order to make the different treatments as realistic as possible (see Table 1 in the Appendix for typical PGRs and UGRs used in the survey). The online-questionnaire was pre-tested with a sample of 24 Amazon users. An online-survey platform was used to present our instructions, the filtered Amazon web pages with PGRs and UGRs as well as our questionnaires. The online-survey was communicated to the respondents via e-mail. E-mail addresses of 2,000 consumers were randomly collected from multiple web addresses using an e-mail extractor program. Invitation e-mails were sent to the selected consumers, explaining the purpose of the study and requesting their participation. To motivate them to participate, respondents were offered incentives in the form of 10 Amazon vouchers (each worth €50) and a report that summarized the results of the survey.

An introduction to the study's context was presented on the online-survey platform. Participants were told that Amazon was planning to overhaul some features on their website and that the study was designed to evaluate customers' experiences with these features and their overall usage behavior. They were further instructed to assume that they had happened to come across several web pages on Amazon that provide specific website-related features and that the following information would be all the information available for further evaluations (i.e. product selection and website assessment) on Amazon. After completing an online pre-experiment questionnaire containing questions on the subjects' demographic information (i.e. age, gender, Internet/e-Commerce usage, and familiarity with Amazon), participants were redirected to a simple default Amazon home page provided by AmaFilter.

Given that we expected some variability in the level and context of participants' online shopping experiences, we created a simple default Amazon home page showing a list of "New and Future Releases" with links related to a selected number of digital video cameras. This was done to allow participants to establish a common frame of reference, and is consistent with Helson's argument associated with adaptation-level theory (Helson 1964). On subsequent web pages, we randomly assigned participants to two groups. The first group had access to web pages with product information including PGRs only, the second group to web pages with UGRs only. Support for UGRs (i.e. consumer reviews and discussion groups) was provided by randomly aggregating them onto one product page for each video camera. The provision of PGRs included, for example, a set of recommendations (usually a list of three to four similar products) prefaced by phrases such as "Customers who bought this title also bought …" and "What do customers ultimately buy after viewing this item? …". There was also a hyperlink at the end of the recommended products to let the customer access a more detailed list of recommendations on a separate page, should the participant be interested in more recommendations. After having inspected the respective treatments, the participants were asked to choose a product that should be provided for a friend as a gift. Finally, after selecting a product, each participant was redirected to the survey platform again and asked to fill out a questionnaire in order to assess his/her experience with the 'revised' website features in terms of PU, TB, PAQ and BI (see Table 2 in the Appendix).

Of the 2,000 consumers invited to participate, 234 e-mails were returned undeliverable. Our final data set contained 366 respondents (189 PGRs and 177 UGRs) resulting in an effective response rate of 15 percent which was deemed a good response rate for an online-survey (Pavlou 2003). Non-response bias was assessed by verifying that early and late respondents were not significantly different (Armstrong and Overton 1977). Early respondents were those who responded within the first two weeks. We compared both samples based on their demographics (i.e. age, gender, Internet experience, and familiarity with Amazon). T-tests between the means of the early and late respondents showed no significant differences (p>0.05), and the demographics of our sample (see Table 3 in the Appendix) were similar to the demographics of typical Internet user populations (von Abrams 2009; Johnson 2005).

Study 2: Laboratory experiment

We additionally tested our hypotheses via a laboratory experiment. 161 participants were recruited among undergraduate and graduate students of a public German university and randomly assigned to two experimental recommendation treatments (PGR treatment: 81 subjects; UGR treatment: 80 subjects). As in study 1, we used AmaFilter to automatically retrieve and filter data from Amazon in order to generate the experimental websites and the corresponding two treatments.

The procedures were comparable to our online-survey in the way that we took the same frame story ("New features on Amazon") to introduce our experiment to the subjects. We first distributed a (paper-based) pre-experiment questionnaire and instructed participants to navigate on several Amazon web pages. Web pages were delivered by AmaFilter that randomly assigned all participants – who were first directed to a common Amazon home page – for the two treatments. The provision of PGRs and UGRs was identical to the setting in study 1 (see Table 1 in the Appendix). Similar to study 1, and after having inspected the product pages, participants were instructed to choose a product that should be sent as a gift to a friend. At the end of the experiment, each subject was asked to complete a paper-based questionnaire to assess his/her experience with the features in terms of PU, TB, PAQ and BI (see Table 2 in the Appendix). During the whole experiment, three research assistants continually monitored the experimental website to ensure that the filtered web pages worked as intended for all conditions. Each participant was guaranteed a monetary compensation for his or her participation (€10). In order to motivate participants to view the experiment as a real-life shopping task and to increase their involvement, they were told at the beginning that their choices would be assessed after the experiment by a digital camera expert.

In the pre-experiment questionnaire, participants were asked about their familiarity with personal computers, the Internet and online shopping and their Internet usage habits (see Table 3 in the Appendix). No significant differences were found among subjects randomly assigned to the experimental groups (p>0.05). In addition, no significant differences were found among groups with respect to participants' age and gender (p>0.05). On average, participants spent 18.3 hours per week using the Internet and had shopped online five times on average in the preceding 12 months. To avoid potential biases in their evaluations, only individuals who did not already own or had not bought digital cameras were invited to participate in the study. This filtering was justified because most consumers may need extra shopping advice when they first buy a product such as a digital camera, and do not have sufficient expertise and experience (Wang and Benbasat 2007).

Measurement of constructs and instrument validation in online-survey and experiment

We used validated scales for all constructs in both studies, with minor wording changes (all measurement items are listed in Table 1 in the Appendix). Measures for PAQ were adapted from Zhang and Li (2004) and measures for TB in a RF were adapted from McKnight et al. (2002b). We used TB as an integrated construct comprising all three sub-dimensions identified in the literature (i.e. competence, benevolence, integrity). As the study focused on the differential effects of PGRs and UGRs on trusting beliefs as a whole, we did not further specify the relationships to TB's sub-dimensions. Measures for PU and BI were adapted from Davis (1989). Because constructs were measured with multiple items, summated scales based on the average scores of the multi-items were used in group comparisons. All questionnaire items for both studies were measured on Likert-type scales anchored at (1) = strongly disagree, (4) = neutral, and (7) = strongly agree.

The reflective first-order measurement models and second-order measurement model (i.e. PAQ) of our two studies were validated using recommended validation procedures (Chin 1998; Wetzels et al. 2009). Items of scales in a related domain were pooled and factor-analyzed to assess their convergent and discriminant validity. While convergent validity was determined both at the individual indicator level and at the specified construct level, discriminant validity was assessed by analyzing the average variance extracted and inter-construct correlations. All standardized factor loadings were significant (p<0.05) (see Table 1), thus providing evidence of *convergent validity*. Construct reliability was assessed by computing the composite reliability for each construct. All constructs had a composite reliability above the cutoff value of 0.70. Further, all reflective constructs met the threshold value for the average variance extracted (AVE>0.50). *Discriminant validity* was assessed by verifying that the square roots of AVEs exceeded inter-construct correlations (see Table 4 in the Appendix). The same validation procedures were applied to the measurement models of PGR and UGR sub-samples in both studies. All constructs in these measurement models also satisfied the reliability and validity criteria mentioned above (presentation of these measurement models is omitted here for brevity).

Table 1. Assessment of Measurement Model: Factor Loadings and Reliability

Constructs	Number of indicators	Range of Standardized Factor Loadings[1]		Composite Reliability		AVE	
		S1[2]	S2[2]	S1	S2	S1	S2
BI	3	.933 – .982	.939 – .973	.977	.967	.934	.924
PU	4	.922 – .939	.920 – .935	.964	.963	.871	.868
TB	9	.785 – .900	.831 – .901	.960	.967	.726	.765
PAQA	5	.814 – .925	.830 – .927	.950	.953	.788	.803
PAQS[3]	5	.852 – .955	.857 – .956	.955	.960	.808	.813
PAQP	5	.797 – .909	.810 – .917	.931	.937	.731	.777
PAQU[3]	5	.783 – .957	.789 – .918	.945	.966	.775	.781
PAQ[4]	20	.915 – .959	.916 – .964	.981	.974	.723	.710

[1] All factor loadings are significant ($p<0.05$); [2] S1 = Study 1, S2 = Study 2; [3] Reverse coded items
[4] Second-order latent variable based on 4 reflective first-order latent variables PAQA, PAQS, PAQP and PAQU and measured with the approach of repeated indicators known as the hierarchical component model (Wetzels et al. 2009)

To test for common method bias, we first applied a Harmon's one-factor test (Podsakoff and Organ 1986). We performed an exploratory factor analysis on all variables, but no single factor was observed and no single factor accounted for a majority of the covariance in the variables. Further, a correlational marker technique was used, in which the highest variable from the factor analysis was entered as an additional independent variable (Richardson et al. 2009). This variable did not create a significant change in the variance explained in the dependent variables. Both tests indicate that common method bias may not have significantly affected our results.

Empirical Analysis

Independent sample t-tests were performed to examine the differential effects of PGRs and UGRs on PU, TB, and PAQ. Structural models of both studies were assessed via partial least squares (PLS) software (Ringle et al. 2005).

Differential effects of PGR and UGR on TB, PAQ, and PU

Results of the independent sample t-tests on PU, TB, PAQ and BI in both studies, together with the means and standard deviations for each condition, are summarized in Table 2.

Table 2. T-Tests on the Aggregated Scores of the Dependent Variables

	Dependent variables	*Recommendation function*	*N*	*Mean*	*S.D.*	*t-value*	*p-value*
Study 1	PU	PGR	189	4.91	1.09	5.29	0.00
		UGR	177	4.21	1.43		
	TB	PGR	189	3.95	1.34	-7.03	0.00
		UGR	177	4.83	1.02		
	PAQ	PGR	189	3.68	0.97	-5.71	0.00
		UGR	177	4.45	1.56		
	BI	PGR	189	4.78	1.14	-0.62	>0.05
		UGR	177	4.85	1.02		

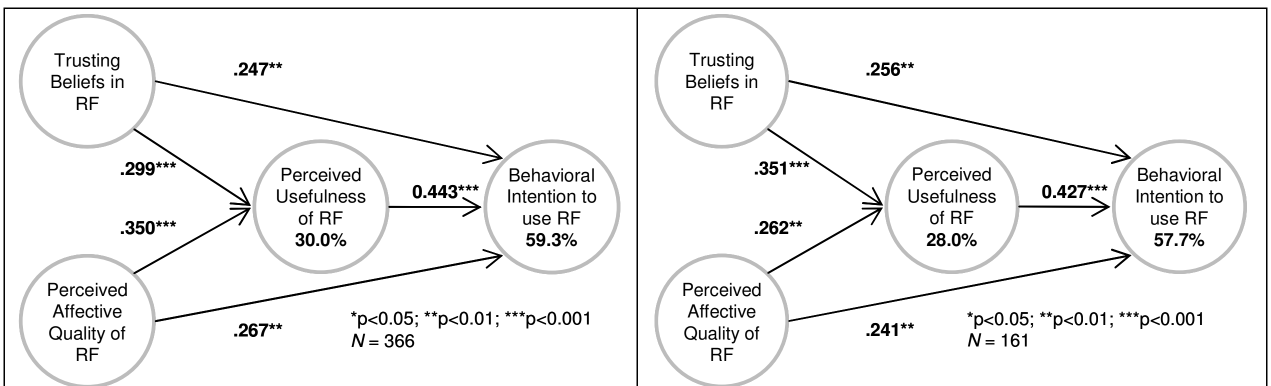
Table 2. T-Tests on the Aggregated Scores of the Dependent Variables (Continued)

	Dependent variables	*Recommendation function*	*N*	*Mean*	*S.D.*	*t-value*	*p-value*
Study 2	PU	PGR	81	5.01	.89	4.24	0.00
		UGR	80	4.46	.75		
	TB	PGR	81	3.78	1.20	-7.35	0.00
		UGR	80	5.12	1.11		
	PAQ	PGR	81	3.45	0.98	-6.72	0.00
		UGR	80	4.68	1.32		
	BI	PGR	81	4.65	0.95	-0.90	>0.05
		UGR	80	4.71	1.16		

In both studies, subjects perceived PGRs as being more useful than UGRs in helping them to perform the task. Conversely, subjects perceived UGRs to have a higher level of affective quality than PGRs. Likewise, participants reported significantly higher trusting beliefs in the presence of UGRs than in the presence of PGRs. Overall, our results support hypotheses H1-H3. Although it was not the focus of hypotheses testing, we examined the direct effects of PGRs and UGRs on BI in a post-hoc analysis and found for both studies that there is no significant difference across the RF types investigated in our study.

PLS analysis

Analyzing the total (pooled) samples (see Figure 2), 59.3% of the variance in BI is explained by the research model in study 1, 30.0% of PU is explained by PAQ and TB together. In study 2, 57.7% of the variance in BI is explained by the model and 28.0% of the variance in PU is explained by PAQ and TB together. As shown in Figure 2, regardless of the data collection method (i.e. field survey versus laboratory experiment) and underlying sample, the hypothesized paths from TB and PAQ to PU and RF usage intentions are significant, indicating that PU partially mediates TB's and PAQ's impact on BI. As expected, PU also significantly affects RF usage intentions.



Study 1 | Study 2

Figure 2. PLS Analysis of Pooled Samples

Assessing PGR and UGR sub-samples of our two studies (see Table 3) in the nomological network of the research model, we found for study 1 that 56.8% of the variance in BI and 34.6% of the variance in PU are explained in the PGR sample, while 61.3% (BI) and 27.7% (PU) are in the UGR sample. For study 2, we found that 53.2% in the variance of BI and 31.4% in the variance of PU are explained in the PGR sample, whereas 59.5% (BI) and 25.1% (PU) are explained in the UGR sample. All path coefficients in both sub-samples were significant ($p<0.05$), supporting hypotheses H4-H8. Interestingly, the path coefficients for the relationships between TB and BI as well as between PAQ and BI were consistently stronger in the UGR than in the PGR sub-sample, while it was the opposite for the relationship between PU and BI.

Table 3. PLS Analysis of Sub-samples (PGR vs. UGR)

Sub-samples		R^2		*Path coefficients*				
		PU	*BI*	*TB → PU*	*PAQ → PU*	*TB → BI*	*PAQ → BI*	*PU → BI*
Study 1	PGR (*N=189*)	34.6%	56.8%	0.33***	0.39***	0.19*	0.21*	0.53***
	UGR (*N=177*)	27.7%	61.3%	0.23*	0.25**	0.31***	0.33***	0.28**
Study 2	PGR (*N=81*)	31.4%	53.2%	0.38***	0.30**	0.22*	0.19*	0.51***
	UGR (*N=80*)	25.1%	59.5%	0.20*	0.19*	0.31***	0.29***	0.27**

*p<0.05; **p<0.01; ***p<0.001

In addition, Table 4 indicates the effect sizes f^2 for both studies (i.e. for PGR and UGR sub-samples respectively) highlighting the differing importance of PU, TB and PAQ as influencing factors of BI in different contexts. Cohen's effect size f^2 is an indicator for the change in R^2 when one latent exogenous variable at a time is excluded from the analysis (Cohen 1988). f^2-values of 0.02, 0.15 and 0.35 indicate whether an exogenous variable has a weak, moderate, or substantial effect, respectively, on the endogenous variable with which each is associated (Chin 1998).

Table 4. Effect sizes

			PU	***TB***	***PAQ***
f^2 (R^2delta) related to BI	Study 1	PGR	0.36	0.10	0.11
		UGR	0.19	0.23	0.24
	Study 2	PGR	0.29	0.12	0.10
		UGR	0.14	0.22	0.21

Overall, PU has substantial effect sizes in both PGR sub-samples and moderate effect sizes in the UGR sub-samples. TB and PAQ have moderate to substantial effective strengths in the UGR sub-samples and weak to moderate effect sizes in the PGR sub-samples. TB and PAQ have larger effect sizes in the UGR than in the PGR samples and therefore exert a stronger influence on BI in an UGR context. Conversely, PU has a larger effect size in the PGR than in the UGR samples and thus has a stronger impact on BI in a PGR context.

Discussion

Previous studies on the design of RFs overlooked the differential cognitive, affective and relational effects of PGRs and UGRs in shaping consumers' online experience. As such, the primary objective of this paper was to compare the relative impact of two e-Commerce RF types (i.e. PGRs and UGRs). Our findings provide insights for researchers who wish to develop a more holistic understanding of the theoretical paths by which different RF types affect cognitive, affective and relational beliefs. The findings are also useful to managers who wish to design sales efficient e-Commerce websites that enhance online-consumers' overall shopping experience at the same time.

From a theoretical perspective, this is the first empirical study comparing the differential effects of PGRs and UGRs on consumers' beliefs and intentions. A main contribution of the paper is a finer-grained understanding of the impact of PGRs and UGRs on consumers' TB, PAQ and PU of RFs and how these different types of consumer perceptions translate into intentions to use the RF. Other studies have either examined the effects of different RF types on single evaluation criteria (such as sales (Park et al. 2009) or social presence (Qiu and Benbasat 2009)) or the effects of one RF type on many evaluation criteria (such as different components of trusting beliefs (Wang and Benbasat 2007)). Though such findings are important, the e-Commerce product recommendation literature had not yet theorized about how PGRs and UGRs differed on their impact on relational, affective and cognitive aspects of consumer beliefs. By drawing on various research disciplines, this study provides new theoretical perspectives that expand our understanding regarding the effect of PGRs and UGRs on individual shopping behavior. Notably, this study demonstrated that not all RF types are equally conducive in influencing TB, PAQ and PU, suggesting the existence of superior effect mechanisms for different RF types. More specifically, UGRs are superior to PGRs in influencing TB and PAQ, while PGRs have stronger effects on PU. Our results also show that PU is the predominant driver of BI in a PGR setting, while TB and PAQ are relatively stronger than PU in affecting BI in an UGR context.

By integrating TB and PAQ with traditional TAM constructs, this study showed that though PU is a strong antecedent of BI on an aggregate level, TB and PAQ are also important (direct and indirect) predictors of BI, and have been found to be stronger predictors of BI in an UGR context. While TB in RFs have previously been shown to influence PU and BI (e.g. Qiu and Benbasat 2009), this study is the first to extend the concept of PAQ to the e-Commerce product recommendation setting. Our findings suggest that primitive affective effects on BI are both partially mediated by cognitive factors, but also have a direct effect on BI which is an interesting finding for a mainly utilitarian IS such as an e-Commerce website. Previous studies found that higher-order affective consumer perceptions such as perceived enjoyment directly affect a consumer's urge to buy impulsively in online-shopping (Parboteeah et al. 2009). Given that this study found a direct positive link between PAQ and BI, future research may further investigate how affection-based usage intentions of RFs translate into actual (impulsive) buying behavior.

From a practical perspective, our results provide guidance for online-retailers who wish to design effective RFs that provide users with a comprehensive shopping experience taking into account cognitive effects together with trust and emotions. E-Commerce website providers may benefit from this study by highlighting different RFs along the purchasing funnel (Riesenbeck and Perrey 2009), which describes the consumer-product interaction process as broken into four successive steps: awareness, consideration, purchase, and loyalty. Depending on their strategic orientation concerning product categories (e.g. experience vs. information goods), channels (e.g. Internet vs. mobile) and customer segments (e.g. younger vs. older consumers), online-retailers should assess which types of consumer reactions are most beneficial to increase sales, and also increase customer stickiness and satisfaction. Accordingly, they could adjust the provision of PGRs and UGRs on their e-Commerce platform. Alternative site designs can be tested using the study's insights to better determine at which stage of the purchasing process PGRs and UGRs should be used on a website to optimally shape consumer's online experience and increase sales.

Limitations and Future Directions

This study contains several limitations. First, because the study's data is not longitudinal, further research is needed to confirm the direction of causality between the proposed constructs. While we feel that results of our two studies support the idea that cognitive, affective and relational aspects of consumer reactions influence behavioral intentions, longitudinal research would help researchers better understand the temporal relationships between all constructs included in the study. Second, we did not examine the effect of perceived ease of use (PEOU) on BI in this study because we chose to only focus on those constructs that have consistently been shown to affect usage intentions across different IS types (e.g. Qiu and Benbasat 2009). Previous research, however, has shown that PEOU can be a stronger predictor of usage intentions than PU for the context of hedonic IS (van der Heijden 2004). Since most e-Commerce websites contain hedonic elements that are also part of recommendation functions (e.g. funny stories told in UGRs, pictures and videos provided in PGRs) and since the interface design and output format of PGRs and UGRs differ considerably, future research should examine how PGRs and UGRs may create different levels of PEOU. Similarly, since the focus of our study was to examine and compare the cognitive, affective and relational effects of PGRs and UGRs, we did not further investigate whether the effects of PGRs and UGRs on BI differed significantly across these two RF types. Future research may also look into how and why PGRs and UGRs may (directly) evoke different levels of BI. Third, the research model was tested in one context (i.e. Amazon.com) involving a specific product type (i.e. digital video cameras). Additional tests with different products (e.g. books or toys) on less well-known e-Commerce websites are necessary to determine if product type and the popularity of the e-Commerce website could alter the proposed relationships. In addition, other (moderating) variables (e.g. user characteristics or vendor attributes) should be examined in future research studies to shed light on the boundary conditions of the investigated relationships. Fourth, our findings must be interpreted in light of the limitations of self-reported data. In this regard, and though intentions to use recommendation functions are a good predictor of actual usage behaviour, they do not equal actual usage behavior. As such, practical implications of the study's results should be interpreted with care, and future studies need to integrate objective data measuring consumers' RF usage behavior and also their buying behavior based on RF usage. Finally, this study has not analyzed the impact of a combination of different RFs (i.e. PGRs and UGRs combined) on consumer perceptions and behavior. Communication research has shown that combining narrative and statistical forms of communication enhances the persuasiveness of a message (Allen et al. 2000). Future studies should examine whether the right mix of RF types on (different) e-Commerce websites would achieve desirable effects at different stages of consumers' buying process.

In summary, interactions with different kinds of online RFs have been recognized as an important topic in e-Commerce. As users' trusting beliefs and affective needs are increasingly found to directly affect their assessment of a technology's usefulness and intentions to adopt the technology, RFs will more likely be accepted and used by online shoppers if they are perceived to allow for a trusting and exciting interaction experience. Additional studies in this area may help researchers extend their understanding of how people interact with and respond to different types of RFs at different stages of the purchasing process, and also benefit e-Commerce retailers by helping them creating more efficient sales platforms and more comprehensive and satisfactory experiences for their customers.

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Appendix

Table 1. Types of provider- and user-generated recommendation functions used in our studies

Recommendation functionalities		***Picture***
Provider-generated recommendations (PGRs)	Customers who bought this item also bought …	
	What do customers ultimately buy after viewing this item?	
User-generated recommendations (UGRs)	Customer discussions	
	Customer reviews	

Table 2. Measurement of reflective variables (Original questionnaire was provided in German)

<table>
<tr><th>Constructs</th><th colspan="2">Indicators</th><th>Source</th></tr>
<tr><td rowspan="3">Behavioral intention to use RF</td><td colspan="2">B1: I intend to continue using the recommendation function in the future.</td><td rowspan="3">Davis 1989</td></tr>
<tr><td colspan="2">B2: I predict my use of the recommendation function to continue in the future.</td></tr>
<tr><td colspan="2">B3: I plan to continue using the recommendation function in the future.</td></tr>
<tr><td rowspan="4">Perceived Usefulness of RF</td><td colspan="2">PU1: Using the recommendation function enables me to find products I want more quickly.</td><td rowspan="4">Davis 1989; Wang and Benbasat 2005</td></tr>
<tr><td colspan="2">PU2: Using the recommendation function enhances my effectiveness in finding suitable products.</td></tr>
<tr><td colspan="2">PU3: If I use the recommendation function, I will increase the quality of my judgments.</td></tr>
<tr><td colspan="2">PU4: Using this recommendation function allows me to accomplish more analysis than would otherwise be possible.</td></tr>
<tr><td rowspan="9">Trusting beliefs in RF</td><td colspan="2">TB1: The recommendation function was competent in recommending digital cameras.</td><td rowspan="9">McKnight et al. 2002a</td></tr>
<tr><td colspan="2">TB2: The recommendation function performed its role of recommending digital cameras very effectively.</td></tr>
<tr><td colspan="2">TB3: Overall, the recommendation function supported me to find suitable digital cameras.</td></tr>
<tr><td colspan="2">TB4: I believe that the recommendation function's dealings with me were in my best interest.</td></tr>
<tr><td colspan="2">TB5: The recommendation function's dealings with me felt like that it would do its best to help me.</td></tr>
<tr><td colspan="2">TB6: I believe the recommendation function's recommendations to me were truthful.</td></tr>
<tr><td colspan="2">TB7: I would characterize the recommendation function's dealings with me as honest.</td></tr>
<tr><td colspan="2">TB8: The recommendation function appeared to be unbiased.</td></tr>
<tr><td colspan="2">TB9: The recommendation function is sincere and genuine.</td></tr>
<tr><td rowspan="3">Perceived Affective Quality of RF</td><td colspan="2">Please, rate how accurately each word describes the RF (on a 7-point Likert-scale)</td><td></td></tr>
<tr><td>Arousal quality
▪ PAQA1 intense
▪ PAQA2 arousing
▪ PAQA3 active
▪ PAQA4 alive
▪ PAQA5 forceful</td><td>Sleepy quality
▪ PAQS1 inactive
▪ PAQS2 drowsy
▪ PAQS3 idle
▪ PAQS4 lazy
▪ PAQS5 slow</td><td rowspan="2">Zhang and Li 2004; Russell and Pratt 1980</td></tr>
<tr><td>Pleasant quality
▪ PAQP1 pleasant
▪ PAQP2 nice
▪ PAQP3 pleasing
▪ PAQP4 pretty
▪ PAQP5 beautiful</td><td>Unpleasant quality
▪ PAQU1 dissatisfying
▪ PAQU2 displeasing
▪ PAQU3 repulsive
▪ PAQU4 unpleasant
▪ PAQU5 uncomfortable</td></tr>
</table>

Table 3. Socio-demographic data

Study	*Age (Mean)*	*Gender*	*Extent of PC/Internet/E-Commerce usage (Mean) (Likert scale 1 to 5)*	*Familiarity with Amazon (Mean) (Likert scale 1 to 5)*
Survey (E-Commerce consumer sample)	28.6	46% female 54% male	PC/Internet: 4.7 / 4.5 e-Commerce: 3.7	"Familiar with Amazon" 3.6 "Visit Amazon regularly" 3.4
Experiment (student sample)	22.3	49% female 51% female	PC/Internet: 4.4 / 4.2 e-Commerce: 2.8	"Familiar with Amazon" 2.8 "Visit Amazon regularly" 2.7

Table 4. Inter-Construct-Correlation Matrix

Constructs	(1) [1]		(2)		(3)		(4)	
(1) BI	**0.97**	**0.96**	--	--	--	--	--	--
(2) PU	0.68	0.66	**0.93**	**0.93**	--	--	--	--
(3) TB	0.56	0.55	0.45	0.45	**0.85**	**0.88**	--	--
(4) PAQ	0.58	0.50	0.48	0.38	0.42	0.24	**0.85**	**0.84**

Note: [1] Study 1 values are presented in left columns, study 2 values in right columns; Bolded diagonal elements are the square root of average variance extracted (AVE). These values should exceed inter-construct correlations (off-diagonal elements) for adequate discriminant validity