DIFFERENTIAL EFFECTS OF PROVIDER RECOMMENDATIONS AND CONSUMER REVIEWS IN E-COMMERCE TRANSACTIONS: AN EXPERIMENTAL STUDY

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Abstract
Despite the importance of online product recommendations (OPR) in e-Commerce transactions, there is still very little understanding about how different recommendation sources affect consumers’ beliefs and behavior, and whether these effects are additive, complementary or rivals for different types of products. This study investigates the differential effects of provider recommendations (PR) and consumer reviews (CR) on the instrumental, affective and trusting dimensions of consumer beliefs, and show how these beliefs ultimately influence continued OPR usage and product purchase intentions. This study tests a conceptual model linking PR and CR to four consumer beliefs (perceived usefulness, perceived ease of use, perceived affective quality, and trust) in two different product settings (search products vs. experience products). Results of an experimental study (N = 396) show that users of PR express significantly higher perceived usefulness and perceived ease of use than users of CR, while users of CR express higher trusting beliefs and perceived affective quality than users of PR, resulting in different effect mechanisms towards OPR reuse and purchase intentions in e-Commerce transactions. Further, CR were found to elicit higher perceived usefulness, trusting beliefs and perceived affective quality for experience goods, while PR were found to unfold higher effects on all of these variables for search goods.

Keywords: Online product recommendations, provider recommendations, consumer reviews, e-Commerce, technology acceptance and usage, perceived usefulness, trusting beliefs, perceived affective quality.
Introduction

As opposed to offline retail channels, e-Commerce consumers cannot try out products before making purchases, which significantly increases their level of uncertainty regarding the quality of the products, and thus hinders their purchasing decisions. To compensate for the absence of quality inspections in online markets, many e-Commerce vendors provide system-filtered recommendations (herein called provider recommendations) that recommend products to consumers based on their past buying behavior or on the preferences of other like-minded consumers. However, product recommendations may also stem from reviews written by consumers about the quality of products based on personal experiences with the products (herein called consumer reviews). Due to their high level of acceptance among consumers, different types of IT-enabled provider recommendations (PR) and consumer reviews (CR) – defined in this paper as different types of online product recommendations (OPR) – are becoming increasingly available on web sites to provide customers with shopping assistance, improve their decision quality, and help buyers and sellers reduce information overload [69]. It is noteworthy that the role of OPR is important for both consumers and suppliers as they represent a critical encounter tool for value co-creation [109]. It is estimated that at least 43% of e-Commerce web sites already offer PR and CR [36]. However, and though the number of different forms of OPR on e-Commerce web sites has exploded in recent years, there is still confusion about PR’s and CR’s isolated effectiveness and about their differential effects on users’ beliefs and behavior. OPR that allow customers to evaluate products and services are thought to significantly affect customers’ decision making and behavior [16, 42]. As such, understanding the decision process and particularly the effect of consumers’ perceptions and beliefs on OPR usage intentions and product purchasing behavior becomes critical to the success of e-Commerce platforms. The present paper aims at answering the following questions: are consumers more responsive to
recommendations generated by the e-Commerce provider through sophisticated agent technology or are they more inclined to follow recommendations generated by other consumers (“human agents”)? More specifically, how do the two sources of recommendations (i.e., PR and CR) compare in evoking consumers’ instrumental, affective and trusting beliefs and ultimately affecting their subsequent OPR usage continuance and product purchase intentions? Are they complements or substitutes in their respective effect mechanisms? Though the study of the effects of OPR on individual product choice or other outcome criteria is not a new field of research [26, 51, 55, 57, 76, 87, 104], there has been very little emphasis on unraveling the differential instrumental, affective and trusting effects of PR and CR on e-Commerce web sites for different product types and assessing how these effects translate into OPR reuse and product purchase intentions. Addressing this gap is conceptually useful because it re-examines accepted relationships [102] between single OPR effects on different sets of beliefs and behaviors, and provides as such a finer grained knowledge about the different mechanisms affecting OPR reuse initiated by different information sources. It also proposes a more holistic and integrative understanding of the effect range of different OPR, which has been overlooked in previous OPR literature. On the other hand, it may also provide e-Commerce vendors with actionable guidelines regarding the positioning and salience of OPR for different product types at different stages of a consumer’s buying process.

By investigating the effects of two different recommendation sources in an extended technology acceptance model (TAM) including instrumental, affective and trusting dimensions of consumer beliefs, the present study extends previous research literature related to the effects of OPR on consumer beliefs and behavior in three important ways: First, it exposes and dissect the distinct effects of PR and CR by examining their influence on three core belief categories: 1)
instrumental beliefs (i.e., perceived usefulness and ease of use), 2) affective beliefs (i.e.,
perceived affective quality), and 3) trusting beliefs. It also unravels the complementary effect of
PR and CR on the core user beliefs. Second, it examines how these three belief categories
mediate the effect of PR and CR on OPR reuse and product purchase intentions based on OPR
use. Third, it investigates the moderating role of product type (i.e., search vs. experience goods)
on PR and CR which has been neglected in previous OPR studies.

Recommendation Sources: Provider Recommendations vs. Consumer Reviews

Information sources can generally be sorted into one of four groups [87]: (1) Personal source
providing personalized information (e.g., “My sister says that this product is best for me.”); (2)
Personal source providing non-personalized information (e.g., “Other consumers report about
their experiences with a purchased product.”); (3) Impersonal source providing personalized
information (e.g., “Based on my profile or the profile of my affinity group, the e-Commerce
provider’s recommender system suggests this product.”); and (4) Impersonal source providing
non-personalized information (e.g., “According to consumer reports, this is the best product on
the market.”). Though many different recommendation types relying on these various
information sources exist on e-Commerce web sites, this study focuses on two specific
recommendation sources corresponding to information sources (2) (i.e., consumer reviews) and
(3) (i.e., provider recommendations) which are widely deployed on e-Commerce web sites. As
shown in Table 1, PR and CR exhibit different characteristics which are argued in the present
paper to have different effects on individual beliefs and intentions in e-Commerce transactions.
PR 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
[59]. They have been proposed as support tools for consumers at various stages of their decision-
making process. Different types of PR have been developed and are currently used within e-Commerce web sites. Content-based and collaborative-filtering-based recommendations are the most widely used classes of PR [101]. 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 [7]. 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 [9]. 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 [62]. For example, a collaborative filtering-based PR would recommend a book to a consumer because other consumers within the same affinity group (i.e., a group of consumers with similar preferences) purchased the book or rated it highly. PR usually include common product descriptions (e.g., brief description of the contents of a book or album) and the provision of key product attributes (e.g., price, label or overall length of a music album).

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On the other hand, recommendations that are based on user-created digital content such as consumer reviews are not based on system-filtered content but rather on original, first-hand content, where a software system does not interfere with the recommendation generation process (see Table 1). Thus, CR are not generated by information technologies; instead, they are *mediated by them* [109]. Furthermore, CR draw their data points from usage experiences and
opinions that are directly reported by other consumers [21], whereas PR automatically and statistically process past buying behaviors or interest profiles besides providing key product attributes and descriptions. Additionally, since CR cannot be presented in a standardized and consistent layout across consumers, web site providers have less control over the structure of presentation format of CR as they do over PR. While consumer reviews are most often based on text and appear with different text length and numbers of paragraphs, PR are always presented in a consistent layout as designed by the web site provider including text, pictures and sometimes multimedia files (i.e., audio and/or video). Finally, CR are based on few data points (e.g., experiences, opinions) from a low number of fellow consumers, whereas PR aggregate and evaluate many data points stemming from a multitude of fellow consumers within a particular affinity group.

In general, PR are perceived as the provision of more or less personalized product items to consumers. They usually include the presentation of provider-generated product descriptions and key product attributes. On the other hand, consumer reviews are sometimes also used to recommend different product items (e.g., a fellow consumer suggests better product alternatives in a review), their main focus is to provide feedback on a given product item (e.g., recommendations on use of presented product item). Both types of recommendation sources are usually provided in conjunction with each other on e-Commerce platforms.

Though a few studies (e.g., Kumar and Benbasat [57], Smith et al. [89], and Duhan et al. [30]) analyzed the effect of both recommendation types (i.e., PR and CR) on a set of dependent variables, they did not specifically focus on how a comprehensive set of instrumental, affective and trusting beliefs elicited by PR and CR affected continued usage of OPR and purchase intentions. Further, these studies did not examine how the effect mechanisms of different
recommendation sources play out in different product contexts, which is another important focus of the present paper.

**Research Model and Hypotheses**

The study’s research model draws on cognitive psychology, affective psychology as well as on recommendation agent, acceptance and trust literatures.

As shown in Figure 1, our model is TAM-related and includes affective and trusting beliefs in addition to TAM instrumental beliefs to explain individual intentions. The instrumental, affective and trusting beliefs and their relationships with OPR types are based on the classification of user evaluations of OPRs proposed by Xiao and Benbasat [104] which models the influence of OPR on trust (i.e., trusting beliefs), perceived usefulness, perceived ease of use (i.e., instrumental beliefs) and satisfaction (i.e., affective beliefs). These three dimensions could be linked to the concept of ‘motivational affordance’ proposed by Zhang [106] who argues that the different motivational sources of users should be taken into account when designing information systems. In effect, users tend to use and continue to use information systems to fulfill various psychological, cognitive, social, and emotional needs. Hence, the properties of an object (or technology) that support these motivational needs (i.e., the object’s “motivational affordance,” [106], p. 145) can influence whether, how, and how much the object (or technology) will be used.

Perceived affective quality (i.e., affective belief) was included in the conceptual model because it captures an individual’s primitive and multi-faceted affective reactions to OPR. As opposed to perceived enjoyment or satisfaction, which are also considered affective reactions to IT, but
which are situated at a secondary or higher level than perceived affective quality [108], we argue that perceived affective quality allows to capture a more foundational dimension of affective consumer reactions. Further, trusting beliefs were included in the model because past research has shown that users had difficulty in determining whether human and software-based OPR are capable of product screening and evaluation and/or whether such OPR act in the interest of the users or are manipulated by the e-Commerce provider [104]. For example, in a focus group experiment, Andersen et al. [6] found that trust in OPR was the most important expectation users had and that it represented a crucial aspect of a consumer’s interaction with an OPR. As such, users’ trusting beliefs encompass important social and interactional dimensions that ought to be considered when comparing different kinds of user evaluations.

**The Effects of PR and CR on Consumers’ Instrumental, Affective and Trusting Beliefs**

In the context of e-Commerce transactions, empirical research indicates that OPR help consumers manage the overwhelming amount of information and choices available in electronic environments by guiding them to a set of more relevant products that are likely to fit their needs [42, 87]. As such, OPR enable consumers to cope with information overload by reducing their search costs, which also enhances their effectiveness in making satisfying buying decisions [38, 55]. OPR are also perceived as being more than just technologies or tools. They represent virtual decision aids that help execute more effective decisions. The theory of human information processing [88] argues that, because of limitations in their cognitive capacity that include limited working memory and limited computational capabilities, people tend to ‘satisfice’ when processing information and making decisions. This theory also posits that consumers reduce their cognitive burden when 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 in the
second stage the reduced set of products is evaluated in detail. Both PR and CR were found to significantly affect perceived usefulness (PU) of the OPR because of their ability to reduce the cognitive burden of sifting through multiple alternatives which consequently helped better evaluate product items [42, 57]. However, and though the impact of PR and CR on PU has been examined separately in previous research (e.g., [52, 76, 97] for PR; [103] for CR), the distinct effect mechanisms of both types of OPR on PU have not yet been explicitly contrasted. In this study, we argue that PR are more effective in reducing search costs for consumers and have, as a consequence, a stronger impact on PU than CR. This argument is based on cognitive fit theory (CFT) [95], which was initially proposed to explain how matching problem representations (such as tables, graphs, and matrices) to different tasks can improve problem solving. CFT suggests that technology could be used to increase task performance if there is a good fit between the task and the information or problem representation. Such fit is argued to result in more efficiency and effectiveness, manifested as increased accuracy and speed in problem solving. For example, when the information format matches the task, users are able to search the information space more efficiently and have better information recall [46, 48], thus lowering the cognitive costs and increasing the benefits of the interface [50]. Therefore, in order to understand how the cognitive fit between the information representation in PR and CR and the consumer’s task of evaluating different types of recommendations affects OPR reuse and product purchase intentions, it is important to first understand how it directly affects users’ beliefs. Given the above, we expect that an OPR type that presents limited but decision-relevant attributes will be preferred by individuals in terms of PU. Indeed, based on the distinguishing features between PR and CR depicted in Table 1, we believe that PR users can immediately see and evaluate the product’s key attributes (e.g., short description, key features) and their values (e.g., price). In contrast, CR users
must infer both what the most important products attributes are, as well as the different values for each attribute, by scanning all information posted by other users. This process is called intuitive regression [61] and is more cumbersome and inefficient than using PR. Following the same idea, Parboteeh et al. [68] found that task-relevant cues (i.e., all cues that enhance the utilitarian value) of a web site 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 this study, we argue that because they provide more task-relevant cues, PR facilitate and enable the consumer’s buying decision better than CR and will therefore be perceived by the consumer as being more useful [32]. As such,

**Hypothesis 1:** Consumers will perceive greater PU of PR than of CR.

Moreover, as opposed to PR, CR most often include only textual comments and do not contain pictures that would make key product information more accessible [23]. Empirical studies in educational psychology (i.e., reading comprehension) found that the cognitive effort for reading full-text sentences and passages is higher as compared to screening pictures and small chunks of key product information [20]. Given that CR¹ 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 PR are perceived as easier to use in evaluating products and supporting the shopping task than CR. Therefore, PR should increase PEOU more than CR.

**Hypothesis 2:** Consumers will perceive greater PEOU of PR than of CR.

¹ Note that CR usually contains structured and easily distinguishable attributes such as “star ratings”. Nevertheless, we argue that consumers will still need to go through CR’s unstructured text to reach the information that would enable them to confirm or disconfirm the rating’s appropriateness. Such process is then believed to reduce the effect of CR on PEOU as compared to PU. The authors wish to thank an anonymous reviewer for bringing up this point.
IT artifacts (e.g., recommendation agents or E-Mail systems) have been found to generate cognitive and affective arousal in IT users, thus showing both hedonic and utilitarian value of IS [28]. Drawing on consumer research and retailing literature [45], studies related to Internet shopping and e-Commerce OPR have constantly shown that various Web site characteristics enhanced users’ perceptions of hedonic value. Examples of such characteristics are socially rich text contents, personalized greetings and pictures of humans [40, 76]. More generally, the effects of hedonic beliefs have also been identified as important determinants of online customer loyalty [56] and have been found to play at least an equal role as instrumental beliefs [94]. Though some studies investigated the affective impact of OPR in e-Commerce focusing on specific characteristics (such as anthropomorphic elements [76]), to the best of our knowledge, no study has yet explored the differential effects of PR and CR on the hedonic dimensions of OPR.

In this study, perceived affective quality (PAQ) is used to capture the hedonic (i.e., affective) value of consumer’s interaction with OPR. According to Zhang and Li [107], this construct refers to an individual’s perception of an object’s ability to change his or her core affect, and is a neurophysiological state that is consciously accessible as the simplest raw (non-reflective) feeling evident in moods and emotions and underlies simply feeling good or bad, drowsy or energized [83]. Core affect is defined as an integral blend of hedonic or valence value (pleasure–displeasure, i.e., the extent to which one is generally feeling good or bad) and arousal or activation value (sleepy–activated, i.e., the extent to which one is feeling engaged or energized). It is considered to be free of any implied cognitive structures and at the heart of emotion, mood, and any other emotionally charged events [82]. The concept of core affect is similar to what some psychologists call primary emotions that precede higher-order emotional episodes such as anger, fear or enjoyment [19]. In the context of IS research, PAQ helps identify an individual’s
fundamental and primitive affective reactions to an IT and has to be distinguished from secondary or higher-level reactions such as computer anxiety, perceived enjoyment, or satisfaction that capture specific feelings and emotional states [108].

In the context of this study, we argue that CR are likely to produce higher PAQ than PR. Indeed, the stories and narratives of personal experiences including specific examples make up the bulk of what a reader will find in CR [21]. As Deighton et al. [29] 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 [78, 92]. In particular, some studies in persuasion and reading research found that narrative messages are more concrete, persuasive and emotional than statistical information [67, 84]. Without examples, ideas may often seem vague, impersonal, and unemotional. With examples, ideas become specific, personal, and vivid producing arousing feelings. While CR convey first-hand experiences, evaluations and opinions of single or few consumers, PR 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 CR are more likely to stimulate affective responses than PR [21, 68]. Similarly, given that CR often comprise elements of stories (e.g., plot, characters, drama), CR may have a greater ability to generate empathy among users and thus affect consumers via direct emotional “contagion” [22]. In this regard, enthusiasm expressed in CR describing the joys of a particular product could for example directly generate some similar feelings in the minds of the readers [18]. Due to the emotive text quality of CR, consumers can thus become emotionally “immersed” in the e-Commerce web site [40]. In contrast, on most e-Commerce web sites, PR deliver statistical data (e.g., “51% that
viewed this item also bought it”) in conjunction with key product attributes (e.g., price, key features) that are clearly arranged and easy to perceive. Further, PR do not use emotive text nor present product information in a personal story format, which suggests that PR evoke less PAQ for consumers than CR. Therefore,

**Hypothesis 3:** Consumers will perceive greater PAQ of CR than of PR.

In a growing body of IS research, trust has been integrated as an important antecedent to technology acceptance [14, 25, 60]. More specifically, empirical studies of trusting beliefs in an e-Commerce vendor and in OPR reveal that trust plays an important role in directly and/or indirectly (e.g., via PU or PEOU) affecting consumers’ usage intentions [73, 76]. Trust in OPR can be considered an extension of interpersonal trust, because – according to the theory of social responses to computers [77] – people treat technological artifacts as social actors and build up trust and relationships with them [98]. When consumers form their initial trusting beliefs (TB) in OPR, the perceived quality of the information provided in OPR contributes to the cognitive evaluation of the OPR’s trustworthiness. Users make inferences about the OPR’s trustworthiness by reflecting on issues such as the amount and scope of explanatory information it provides, or on how well the recommended products conform to the preference structure users have specified. Users’ TB in OPR can be enhanced when OPR provide additional information in the form of explanations (e.g., how, why and trade-off explanations) to reveal their underlying reasoning process and cognitively justify their recommendations [98].

These findings can be extended to the differential effects of PR and CR on trusting beliefs. We argue that CR are more likely to evoke higher TB in consumers than PR. Indeed, CR on e-Commerce web sites typically include first-hand experiences and explanations of other users that report on how and why they have (or have not) bought the product thereby unfolding their
reasoning process. Moreover, CR 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 by which another user made his or her decision. This transparency of the reasoning process is a key characteristic of CR and may contribute to building up user’s trust [1]. In contrast, the majority of PR typically lack adequate explanation facilities [98]. 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 PR from revealing the underlying reasoning process that govern their decision making and thus prevents them from demonstrating the competence, benevolence and integrity of the OPR. Empirical studies in the e-Commerce OPR literature also found that this kind of information asymmetry (i.e., that a PR has more information than the user with respect to the underlying logic of the PR’s recommendation) hamper consumer trust toward the PR [98].

In addition to product-related information and explanations, other sources are also used by consumers to form their trusting beliefs in OPR, especially by those who have limited product knowledge and therefore cannot accurately appraise the completeness and integrity of the information provided by the OPR. As we compare PR and CR on their differential effects on trusting beliefs, reflecting on the source credibility (i.e., the credibility an OPR conveys with the presented recommendation) may have particular explanatory value. Research on source credibility and source effects of communication has a long tradition in communication, consumer and marketing research. Hovland and Weiss [47] 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. 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 [31]. 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 [89].

The effect of source credibility is also believed to apply to the on-line environment. Wathen and Burkell [99] 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 PR and CR. By definition, CR 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 PR 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 [21], which in turn may decrease consumers’ trusting beliefs in the recommendation. Furthermore, PR may be considered as manipulative in the sense that only one-sided, and always positive, recommendations are presented. By contrast, (both one or a collection of) CR may include multi-sided messages (e.g., positive, neutral, negative) and thus present more complete information which are likely to be perceived as more credible [22].

As such,

**Hypothesis 4:** Consumers will have higher TB in CR than in PR.
The Moderating Role of Product Type: Search vs. Experience Goods

Given that usage behavior, task performance, and decision outcomes change as product type changes [40, 63], this study examines the moderating effect of product type on the relationships between OPR use and the different consumer beliefs. Product type has been studied extensively in decision-making research, where it has frequently been categorized into search and experience goods based on the possibility for consumers to assess the key qualities of a product before purchasing and consuming it [17, 64, 87]. According to Nelson [64], perceived quality of a search good involves attributes of an objective nature, while perceived quality of an experience good depends more on subjective attributes that are a matter of personal taste. Weathers et al. [100] categorize goods according to whether or not it is necessary to go beyond simply reading information to also use one’s other senses (e.g., listen online to a 30-second clip from a music CD) to evaluate quality. The evaluation of search goods is primarily associated with a fact-gathering, knowledge-seeking stance that is typically outcome-oriented, concentrated, impersonal, and objective [65]. On the other hand, the evaluation of experience goods is rather comparable to an engaging expedition that is process-oriented, personal, and subjective [86]. In light of these studies, search goods can be characterized as products that can easily be evaluated and compared based on objective key attributes before making a purchase decision. While the evaluation of search goods can be supported by experiential elements2 (e.g., photos or videos demonstrating the ease of use of a digital video recorder), there is no strong need to use other than visual senses to evaluate quality [63]. Further, it is rather difficult for consumers to assess experience goods before the consumption of the product, as user preferences are formed during rather than before product consumption [87]. Experience goods refer to products in which

2 The authors wish to thank an anonymous reviewer for bringing up this point.
it is relatively difficult and costly to obtain information on quality prior to interacting with the product. In addition, key attributes of experience goods are rather subjective or difficult to compare, and there is often the need to use one’s senses to evaluate quality. As a consequence, experience goods require sampling (e.g., movie trailers, software trial versions) or purchase in order to evaluate product quality [63]. Typical examples of search goods include furniture [65] and calculators [87], and examples of experience goods include music [17] and wine [54]. Although all products involve a certain mix of search and experience attributes, the categorization of search and experience goods continues to be relevant and widely accepted [49]. The difference between search and experience products can inform our understanding about the effectiveness of OPR types when considering different product types. When evaluating OPR, different instrumental, affective and trusting beliefs are elicited that influence consumers’ preferences. More specifically, there may be an interaction between product type and OPR type, as different product types have differing information needs and thus trigger different instrumental, affective and trusting processes [74] that can be met more or less effectively by different OPR types.

PR on e-Commerce web sites most often provide a lean and well-organized information design with objective key product attributes and statistical data about other consumers’ evaluation and buying behavior (e.g., “80% buy the item featured on this page”) being at the center of their recommendation. Thus, compared to CR, they are more effective at more rapidly providing an overview of key product attributes without including much noise that is irrelevant to the objective product evaluation. Given that search goods, as opposed to experience goods require that objective attributes be evaluated in an outcome-oriented and impersonal fashion, we argue that PR may better match the information needs of search goods [3]. As such,
**Hypothesis 5a:** Product type moderates the effect of OPR use on users’ PU. Use of PR will elicit greater PU in the context of search goods than in the context of experience goods.

As discussed above, taste, emotions and subjective attributes play a larger role in the evaluation of experience goods (such as movies or music) than in the evaluation of search goods [49]. Since it is difficult or even impossible to evaluate experience products before purchase, consumers are usually more inclined to trust and rely on OPR for such products [53]. Given that CR include the experiences and opinions of other consumers, we argue that they better match the information needs for experience goods in terms of providing a transparent reasoning process underlying product acquisition. Similarly, we believe that CR can better fit the information needs of experience goods in terms of eliciting consumers’ affective reactions. As previously discussed, CR most often contain emotive text (e.g., in a story or recounting) leading consumers to become emotionally immersed and engaged in the process of product evaluation. Since experience goods, as opposed to search goods, usually require representations that facilitate more in-depth and personal product evaluations, we argue that CR may be more effective in stimulating affective responses for experience goods rather than for search goods. As such,

**Hypothesis 5b:** Product type moderates the effect of OPR use on users’ TB. Use of CR will elicit greater TB in the context of experience goods than in the context of search goods.

**Hypothesis 5c:** Product type moderates the effect of OPR use on users’ PAQ. Use of CR will elicit greater PAQ in the context of experience goods than in the context of search goods.

**Antecedents of Consumers’ OPR Reuse and Purchase Intentions based on OPR use**

While much OPR research focused on the direct effects of OPR use on decision outcome variables [41, 42, 91], recent studies introduced the mediating effects of the decision process between OPR use and decision outcomes [52]. This is consistent with the theory of planned behavior and the technology acceptance model, which state that the effect of IT (in its various forms and derivatives) on behavioral intention is mediated by behavioral beliefs (i.e., PU and
PEOU) toward the behavior [4, 27]. We expect the same to hold for the effect of PR and CR on behavioral beliefs in the context of e-Commerce platforms.

Several IS acceptance studies have shown that the set of factors (i.e., the different consumer beliefs) representing the decision-making process in this study has a direct effect on behavioral intentions (for PU, see [2, 27, 94]; for TB, see [35, 73, 97]; for PAQ, see [85, 107]). We use intention to reuse the OPR and intention to purchase a product based on the OPR as measures of the impact of OPR use on the decision outcomes. Both outcome factors have been extensively used in business-to-consumer e-Commerce research [37, 56]. Further, the theory of planned behavior suggests that behavioral beliefs such as the decision process variables examined in this paper mediate the effect of external variables on intentions. As such, we expect that the impact of OPR evaluation on reuse and purchase intentions will be mediated by this set of decision process variables. More specifically, we argue that stronger instrumental, affective and trusting beliefs in OPR will increase the likelihood that consumers reuse (i.e., continue paying attention to and leverage) OPR in subsequent product search and evaluation activities. Likewise, we argue that higher PU, PAQ and TB in OPR will translate into increased intentions to purchase products recommended by the OPR due to positive evaluations spilling over from instrumental, affective and trusting cues of OPR [11, 52, 58, 73, 93]. As such,

**Hypothesis 6a:** The effect of OPR use on intention to reuse OPR is mediated by the consumer’s PU of OPR.

**Hypothesis 6b:** The effect of OPR use on intention to purchase is mediated by the consumer’s PU of OPR.

**Hypothesis 7a:** The effect of OPR use on intention to reuse OPR is mediated by the consumer’s PAQ of OPR.

**Hypothesis 7b:** The effect of OPR use on intention to purchase is mediated by the consumer’s PAQ of OPR.

**Hypothesis 8a:** The effect of OPR use on intention to reuse OPR is mediated by the consumer’s TB of OPR.
**Hypothesis 8b:** The effect of OPR use on intention to purchase is mediated by the consumer’s TB of OPR.

For replication purposes, we also re-examine the relationships between PEOU and PU [27, 97], TB and PU [35, 73, 97] and between PAQ and PU [85, 107].

**Research Method**

**Study Design and Context**

The research model depicted in Figure 1 was tested via a laboratory experiment in a $2 \times 2$ between subjects factorial design. Two types of online product recommendations (PR, CR) in conjunction with two different product types (search product: calculators; and experience product: music CDs) were manipulated between subjects [39]. A total of 396 subjects were recruited via e-mail from a German panel of online users (called ‘Socio-Scientific Panel’) maintained by oFb, an open, research-based online survey institution. We chose calculators and music CDs as our products for three main reasons: (1) Calculators have been used as typical search products, music CDs as typical experience products in previous research studies [17, 57, 87], (2) both products have comparable price ranges, are nonessential and similarly appeal to both female and male users, and (3) both products have a relatively high number of product attributes and a large number of alternatives available on the market that requires a certain level of know-how from consumers making the use of OPR more relevant on e-Commerce web sites [76].

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 supports the provision of PR and CR [8, 33]. Similar to previous online-recommendation studies [57], 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 PR and CR in order to make the different treatments as realistic as possible. An online-survey platform was used to present the instructions, the filtered Amazon web pages with PR and CR as well as the pre- and post-experimental questionnaires which had been pre-tested with a sample of 24 Amazon users.

Experimental Procedures, Manipulations and Incentives
The experiment proceeded as follows: an introduction to the study’s context was presented on the online-survey platform. Participants were generally told that Amazon was planning to overhaul some features on their web site (including design, structure, content and functionality of the web site) and that the study was designed to evaluate customers’ experiences with these features and their overall usage behavior during a shopping task (i.e., choosing a product item for a good friend). They were further instructed to assume that they had happened to come across several web pages on Amazon that provide specific web site features and that the following information would be all the information available for further evaluations on Amazon. There was no time limit for the tasks. After completing an online pre-experimental questionnaire containing questions on the subjects’ demographic information (i.e., age, gender, education, household income, familiarity with and usage of Amazon, Internet usage and online shopping experience), 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” of different product items (of calculators and music CDs) and instructed all subjects to evaluate several recommendation pages (including web sites with both PR and CR) that could

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3 The evaluation of recommendation pages in the baseline task included one item of PU, PEOU, TB and PAQ respectively. No significant differences were found between subjects that were later assigned to the four study treatments.
be accessed from the default home page [57]. This was done to allow participants to establish a common frame of reference and start with a baseline experience, and is consistent with Helson’s argument associated with adaptation-level theory [43]. Further, we used this baseline task to collect individual preference data of subjects (i.e., preference profiles) for later use during the experimental tasks in order to generate appropriate PR [15]. This step took 8-16 minutes based on the log-files we analyzed after the experiment. Once they finished the baseline task, the subjects were randomly assigned\(^4\) to one of the four groups pertaining to our 2 x 2 between subjects factorial design\(^5\) (see Table 2).

In their respective experimental conditions, the subjects were then instructed\(^6\) to browse the web site and to locate information on the presented products to become familiar with the web site layout and its recommendation features. After having inspected several product pages, participants were instructed to make a purchase decision for a specific product item (among the available products) that should be sent as a gift to a friend\(^7\). Finally, each subject was asked to complete a post-experimental online questionnaire that recorded his/her evaluations of the OPR features (i.e., PU, PEOU, PAQ and TB) and behavioral intentions. The post-experimental questionnaire also included questions for several manipulation checks.

\(^4\) Random assignment was made using randomized integer numbers generated via the www.random.org API.

\(^5\) Three main reasons explain why we did not combine PR and CR in one of our treatments: First, the focus of our study was to unravel the distinct effects of PR and CR on different core and critical consumer beliefs. Second, our objective was to investigate how different product types modified the effect of PR and CR on those beliefs. Finally, our aim was to extend the study by Kumar and Benbasat [57] by conceptualizing and testing the effect of PR and CR on a larger set of instrumental, affective and trusting beliefs in the context of two product types.

\(^6\) All instructions were depicted on the experimental websites.

\(^7\) Given that similar tasks were successfully used in previous experimental settings [57, 98] and that evaluation of PR and/or CR before product purchases to reduce behavioral uncertainty is a common user behavior in digital environments [104, 109], we believe that the realism of the task used in our experiment is acceptable.
The provision of PR on the experimental web sites included a set of recommendations (usually a list of four to five similar product items) that were generated based on a user-based collaborative-filtering method\(^8\). Following this method, the subject’s preference data collected during the baseline experience task was used to automatically calculate similarities between the subject’s profile and the preference profiles of other users. Based on these data similarities (i.e., preference proximity), other product items of like-minded consumers were suggested to the subjects [15]. The PR on the experimental web sites were prefaced by phrases such as “Customers who bought this title also bought …” and “What do customers ultimately buy after viewing this item? …”. By selecting a specific product item, subjects could access the provider-generated product descriptions and attributes on this recommended item to be able to evaluate the product features. Similar to Kumar and Benbasat [57], support for CR on the experimental web sites was provided by displaying a randomly created sequence of consumer reviews pertaining to a specific product item when the user clicked or moved the mouse over the product item (that he or she could access via searching or browsing the product web sites). To control for review valence and consistent with previous studies [70], the reviews included a random mix of positive, negative and neutral feedback across all subjects in the CR conditions. See Figure 2 for samples of our experimental web sites with PR and CR.

To provide an incentive for the subjects to evaluate the products, the subjects were told that they would be entered into a raffle where they could win the music CD or the calculator they had selected for their friends. Similar to other experimental studies (e.g., [76]), providing extra

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\(^8\) User-based collaborative-filtering techniques collect a consumer’s preferences and compare them to (affinity) groups of people with similar preferences to suggest new product items (e.g., [105]). The recommendations given are personalized in the sense that user-based collaborative-filtering methods take into account the consumer’s and like-minded users’ preferences to suggest other product items.
incentives is very helpful in motivating participants to view the experiment as a serious online shopping session and to increase their involvement.

Survey Instrument and Measurement Models
The survey instrument, which had been translated into German and back-translated into English by a professional translation services firm, used validated scales for all constructs, with minor wording changes (see Table 3). Measures for PAQ were adapted from Zhang and Li [107] and measures for TB in OPR were adapted from Wang and Benbasat [97]. Consistent with previous empirical studies (e.g., [76]), 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 PR and CR on trusting beliefs as a whole, we did not further specify the relationships to TB’s sub-dimensions. Measures for PU were adapted from Davis [27]. Measures for intentions to reuse and intentions to purchase were adapted from prior literature [52, 56]. All questionnaire items were measured on Likert-type scales anchored at (1) = strongly disagree, (4) = neutral, and (7) = strongly agree. Similar to Kamis et al. [52], two binary variables were constructed (i.e., OPR use = 1 for PR, OPR use = 0 for CR; Product type = 1 for search products, Product type = 0 for experience products) to capture the four experimental group conditions.

Data Analysis

Sample Descriptives
As shown in Table 4, our sample can be considered as representative of the entire online customer population in Germany [96]. Almost two thirds of our subjects were between the ages

\[9 \text{ The German version of the survey is available from the authors upon request.} \]
of 20 and 40, 58 percent are female, 68 percent have at least some college/university education, and 64 percent have a household income of over €30,000 per year. In the pre-experiment questionnaire, participants were also asked about their experience and familiarity with Amazon, whether they would regularly visit the Amazon web site, and about their Internet usage and online-shopping habits. On average, participants spent 18.3 hours per week using the Internet and had shopped online 10.4 times on average in the preceding 6 months.

Non-response bias was assessed by verifying that early and late respondents were not significantly different [10]. We compared both samples based on their socio-demographics. T-tests between the means of the early (first 50) and late (last 50) respondents showed no significant differences (p>0.05) indicating that non-response bias was unlikely to have affected the results.

**Controls and Manipulation Checks**
In order to confirm the random assignment of subjects to the different experimental conditions, we performed a multivariate analysis of variance (MANOVA). There were no significant differences in gender (F=1.573, p=0.195), age (F=0.498, p=0.684), education (F=0.183, p=0.908), household income (F=0.577, p=0.631), familiarity with Amazon (F=0.145, p=0.933), usage of Amazon (F=0.153, p=0.928), Internet experience (F=0.996, p=0.349), online shopping behavior (F=0.782, p=0.505), and personal relevance of product types (F=1.345, p=0.271) among the four experimental conditions. These results indicate that participants’ characteristics were not the cause of the differences in consumers’ beliefs and intentions.

Several further manipulation checks were performed. All of the 396 subjects clicked on at least eight hyperlinks to access the online recommendations on the product web sites, indicating that
all of the subjects were exposed to the OPR treatments\textsuperscript{10}. Additionally, the subjects were asked in the post-experimental questionnaire to what extent they had perceived changes (i.e., in design, structure, content or functionality) to the web sites they had visited during the experiment (7-point Likert-scale anchored at (1) = low and (7) = high). All of the four treatment groups recognized these general changes to the web sites and there were no significant differences between the four groups (the means ranged between 5.42 and 5.62; F=1.44, p=0.233). In addition, drawing on items\textsuperscript{11} from Kumar and Benbasat [57], we checked participants’ perceived support for PR and CR in the respective conditions of the experiment. T-test results indicated that our experimental manipulations regarding the provision of the different OPR were successful\textsuperscript{12}. Finally, one hundred percent of the participants assigned to the four treatments also recalled the combinations of recommendation source and product type correctly in the post-experimental questionnaire. Taken together, these results indicate that the treatments were successfully executed. Given that all of our items were measured with the same method, we tested for common method variance using Harman’s one factor test [75]. We performed an exploratory factor analysis on all the 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 [79]. This variable did not create a significant change in the variance explained in the dependent variables. Both tests suggest that common-method bias is unlikely to have significantly affected our results.

\textsuperscript{10} A program routine was developed to record the number of clicks of the hyperlinks and to check whether participants were exposed to specific product items.

\textsuperscript{11} The reliability estimates for perceived support for PR was $\alpha = 0.92$, for perceived support for CR $\alpha = 0.96$.

\textsuperscript{12} For conditions with actual support for PR ($N=201$): Mean difference between perceived support for PR vs. for CR, $t=101.483$, $p<0.000$; for conditions with actual support for CR ($N=195$): Mean difference between perceived support for PR vs. for CR, $t=-78.173$, $p<0.000$. 
Measurement Characteristics

The reflective first-order measurement models and second-order measurement model (i.e., PAQ) were validated using recommended validation procedures [24]. 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 [24, 34]. All standardized factor loadings were significant (p<0.05), 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 [12]. 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. The same validation procedures were applied to the measurement models of PR and CR 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). The factor loadings, values for composite reliability and average variance extracted, and descriptive statistics of all constructs can be seen in Table 5.

Test of Hypotheses

The model was tested via partial least squares (PLS) analysis using SmartPLS 2.0 with the bootstrapping resampling procedure [81]. As shown in Figure 3, consumers were found to perceive significantly greater PU and PEOU of OPR with PR than with CR as indicated by the positive and significant beta coefficients, thus supporting H1 and H2. Conversely, consumers
were found to perceive significantly greater TB and PAQ of OPR with CR than with PR as shown by the negative and significant beta coefficients, thus supporting H3 and H4.

--------- Insert Figure 3 here ---------

The moderating effects of product type were assessed by examining the beta coefficients between product type and the three belief categories. First, while the beta coefficient between product type and PU is positive and significant ($\beta=0.083, p<0.05$), it is not significant for the relationship between product type and PEOU ($\beta=0.012, p>0.05$). Further, the beta coefficients between product type and TB ($\beta=-0.132, p<0.001$) and between product type and PAQ ($\beta=-0.194, p<0.05$) are both negative and significant. Second, the beta coefficients between the interaction term (OPR use × Product type) and the three belief categories are all positive and significant ($\beta=0.471, p<0.001$; $\beta=0.379, p<0.001$; $\beta=0.491, p<0.001$), indicating that product type significantly moderates the relationships between OPR use and the three belief categories. More specifically, PR’s effects on PU are reinforced in the context of search products (as compared to experience products), while CR’s effects on TB and PAQ are strengthened in the context of experience products (as compared to search products), hence supporting H5a-H5c. As shown in Figure 4, the estimated means of PU, PEOU, TB and PAQ were plotted for each of the two product types. The results show that PR are perceived as more useful for search goods than for experience goods. Likewise, trusting beliefs and perceived affective quality towards PR increase when moving from an experience good to a search good. Conversely, CR elicit higher trusting beliefs and perceived affective quality in an experience good than in a search good.

--------- Insert Figure 4 here ---------

The mediating role of user evaluation variables (i.e., different consumer beliefs) between OPR use and the two behavioral intention variables was assessed by performing a Sobel's test [90].
We ran two independent PLS models to generate the required path coefficients and standard errors [66]. The first model included paths from OPR use to the three mediator variables. The second model included paths from the mediator variables to the two behavioral intention variables, as well as paths from OPR use to the behavioral intentions variables. Results show that the effects of OPR use on intentions to reuse the OPR and intentions to purchase were significantly mediated by TB (SobelI2R=-2.177, p<0.05; SobelI2P=-1.970, p<0.05) and PAQ (SobelI2R=-2.844, p<0.01; SobelI2P=-2.476, p<0.05), while they were not significantly mediated by PU (SobelI2R=1.008, p>0.05; SobelI2P=1.017, p>0.05). Given the significant direct path from OPR use to intentions to reuse the OPR ($\beta=0.198$, p<0.01) and intentions to purchase ($\beta=0.171$, p<0.001), it appears that TB and PAQ partially mediate the effects of OPR use on intentions to reuse the OPR and intentions to purchase. In sum, H7a, H7b, H8a and H8b are supported, while H6a and H6b are rejected.

As shown in Figure 5, the effect of the three individual beliefs’ categories on behavioral intentions was assessed for each OPR type sub-sample. In the CR sub-sample, TB and PAQ were found to be the most prevalent consumer beliefs affecting intentions to reuse and intentions to purchase as indicated by their significant beta coefficients and effect sizes. By contrast, PU was found to be the dominant belief influencing intentions to reuse in the PR sub-sample, while intentions to purchase were equally affected by PU and PAQ.

Discussion

The main objective of this paper was to unravel the distinct effects of PR and CR in e-Commerce transactions and to compare the relative impact of two sources of e-Commerce OPR in two different product contexts (i.e., search products vs. experience products). Theoretically, our
findings provide a holistic understanding of the mechanisms by which different OPR types affect instrumental, affective and trusting beliefs. Practically, the findings are potentially useful to managers who wish to design sales efficient e-Commerce web sites that enhance online-consumers’ overall shopping experience.

Specifically, this study provides a finer-grained understanding of the impact of PR and CR on consumers’ PU, PEOU, TB and PAQ of OPR and how these different types of consumer beliefs translate into intentions to reuse the OPR and to purchase based on the OPR. Other studies have either examined the effects of different OPR types on single evaluation criteria (such as sales [71, 72] or social presence [44, 76]) or the effects of one OPR type on many evaluation criteria (such as different components of trusting beliefs [98]). Though such findings are important, the e-Commerce OPR literature had not yet theorized about how PR and CR differ on their impact on instrumental, affective and trusting consumer beliefs. By drawing upon various research disciplines, this study provides new theoretical perspectives that expand our understanding regarding the effect of PR and CR on continued usage of online recommendations and on individual shopping behavior. Notably, our results demonstrated that not all OPR types are equally conducive in influencing TB, PAQ, and PU, suggesting the existence of superior effect mechanisms for different OPR types. More specifically, CR were found to be superior to PR in influencing consumers’ trusting and affective beliefs, while PR were found to have stronger effects on instrumental consumer beliefs. Our results also showed that PU was the stronger driver of intentions to reuse OPR in a PR setting, while TB and PAQ were found to be stronger than PU in affecting both intentions to reuse and to purchase in a CR context. In sum, PR and CR focus on two distinct relationship building orientations. While PR appears to be more effective
for transactional relationships, CR appears to be more efficient for enhancing consumer experiences that build on trust and affections.

Additionally, our study showed that product type exhibited a moderating effect on the relationship between OPR use and consumer beliefs. Specifically, our results showed that TB and PAQ were enhanced in the context of experience products as compared to search products when users based their evaluations on CR, and that PU was more strongly affected in the context of search products as compared to experience products when users based their evaluations on PR. Further, our study found that the effects of OPR use on intentions to reuse and to purchase were mediated by TB and PAQ, but not by PU.

Another important contribution of this study is related to its investigation of two key antecedents of user’s beliefs at the same time: OPR type and product type. While past studies focused on the impact of PU and PEOU on user behavior, less attention had been devoted to the study of PU and PEOU’s antecedents [13]. Also, and though much research has shown that affective and trusting beliefs were important antecedents of user behavior, very little research investigated the characteristics of different OPR types (including different interface designs and content structures) affecting such beliefs. In this regard, our study’s results add to the existing e-Commerce OPR literature by providing a better understanding of how and why OPR use affects decision making.\(^\text{13}\).

From a practical perspective, our results provide guidance to online-retailers who wish to design effective OPR that provide users with a comprehensive shopping experience taking into account instrumental effects together with trust and emotions. E-Commerce web site providers may benefit from this study by proposing or emphasizing different OPR along the purchasing funnel.

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\(^{13}\) See for example propositions on recommendation output characteristics and product-related factors suggested by Xiao and Benbasat [104].
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 or combinations of these are most beneficial to increase sales, and also increase customer stickiness and satisfaction. Accordingly, they could adjust the provision of PR and CR on their e-Commerce platform. Alternative site designs can be tested using the present study’s insights to better determine at which stage of the purchasing process PR and CR should be more or less emphasized on a web site. Our results thus indicate that providing appropriate OPR on a web site can allow customers to enjoy their shopping experience more and perceive the system as improving their decision making process and shopping efficiency. Consequently, customers might increase their online purchases based on the recommendations of OPR and ultimately the reuse of OPR for future purchases.

Some limitations to the present study also need to be acknowledged. First, though the study’s results strongly support the paper’s main argument that instrumental, affective and trusting beliefs need to be considered together in order to reach a deeper understanding of individual intentions in the context of e-Commerce transactions, we believe that longitudinal research will help better understand the temporal and causal relationships between the study’s constructs. Second, given the fact that our research model was tested in the context of one e-Commerce website (i.e., Amazon.com) and involved just two artifacts for search and experience products (i.e., calculators and music CDs), we believe that additional tests including a variety of both search (e.g., furniture, footwear) and experience (e.g., fragrances, wine) products on less well-known e-Commerce web sites would be useful to assess the generalizability of the study’s results.
Moreover, using additional conceptualizations of product type (e.g., high- vs. low-involvement products, physical vs. digital products, etc.) and other, more personalized instantiations of recommendation sources (e.g., content-filtering based provider recommendations and/or consumer reviews including multimedia) would yield complementary insights to those of this study. Additionally, and though we controlled for several important variables (i.e., personal relevance of product types, familiarity with and usage of Amazon and online shopping behavior), we believe that controlling for initial informational needs of users as regards to product attributes or product usage experiences would be useful to validate the effect of the different individual perceptions (i.e., PU, PEOU, PAQ and TB) towards PR and CR found in this paper. Further, and while the study’s constructs exhibit good psychometric properties, we believe that additional work on the scales’ items would be useful to more systematically insure that their wording is not biased towards either type of OPR. Finally, and since combining narrative and statistical forms of communication is believed to enhance the persuasiveness of a message [5], an interesting avenue for future research would be to examine what right mix of OPR types would achieve the optimal results at different stages of a consumer’s buying process.

Conclusion
Online product recommendations have become critical tools for customer online experience enhancement. As hypothesized, the present study found that PR and CR exhibited different effect pathways through which they affected OPR reuse and purchase intentions in the context of search and experience products. Theoretically, the study unraveled the differential effects of PR and CR on three distinct core and critical individual beliefs (instrumental, affective and trusting) influencing individual online transactions. Practically, the study provided interesting insights

14 The authors would like to thank an anonymous reviewer for bringing up this point.
about how PR and CR could be used to foster either transactional or loyalty building relationships. It is hoped that the present study's results will be useful to future research aiming at improving or developing OPR capable of increasing the efficiency of e-Commerce transactions and value co-creation encounters.

References


Figure 1. Research Model
Figure 2. Examples for experimental web sites including PR for calculators (top) and CR for music CDs (bottom)
Figure 3. Results

Figure 4. Means of Perceived Usefulness, Perceived Affective Quality and Trusting Beliefs
Table 1. Characteristics of Provider Recommendations and Consumer Reviews

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Provider Recommendations (PR)</th>
<th>Consumer Reviews (CR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Author/Creator of content</td>
<td><strong>System-filtered</strong> content extracted from statistical analyses; complemented with product item descriptions and key attributes</td>
<td>Other consumers/users</td>
</tr>
<tr>
<td>Originality of content</td>
<td><strong>System-filtered</strong> content extracted from statistical analyses; complemented with product item descriptions and key attributes</td>
<td>Original, first-hand content</td>
</tr>
<tr>
<td>Source of recommendation preferences</td>
<td>Attribute-based preferences based on past consumer <strong>behavior and profiles</strong></td>
<td>Preferences based on past consumer <strong>experience and/or opinions</strong></td>
</tr>
<tr>
<td>Number of data points included in the recommendation</td>
<td>Many (Very large data sets)</td>
<td>Few</td>
</tr>
<tr>
<td>Media richness of recommendations</td>
<td>Text, pictures (, multi-media)</td>
<td>(Predominantly) text-based</td>
</tr>
<tr>
<td>Level of e-Commerce provider’s control over content layout</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>

Table 2. Group Assignment

<table>
<thead>
<tr>
<th>Product type</th>
<th>Provider recommendation (PR)</th>
<th>Consumer review (CR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Search good (SG)</td>
<td>(1) PR x SG (N=103)</td>
<td>(3) CR x SG (N=99)</td>
</tr>
<tr>
<td>Experience good (EG)</td>
<td>(2) PR x EG (N=98)</td>
<td>(4) CR x EG (N=96)</td>
</tr>
</tbody>
</table>
Table 3. Survey Instrument and Descriptive Statistics

<table>
<thead>
<tr>
<th>Construct and Indicators</th>
<th>Descriptives and Standardized factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I2R</strong> Intention to reuse (Cronbach’s $\alpha = 0.847$, CoR = 0.897, AVE = 0.685)</td>
<td>Mean = 5.18, St. Dev. = 0.83</td>
</tr>
<tr>
<td>I2R1 … you needed to purchase a similar product in the future, how likely is it that …</td>
<td>0.827</td>
</tr>
<tr>
<td>I2R2 … you would predict your use of this type of OPR to continue in the future?</td>
<td>0.842</td>
</tr>
<tr>
<td>I2R3 … you plan to continue using this type of OPR in the future?</td>
<td>0.792</td>
</tr>
<tr>
<td>I2R4 … you would continue to pay attention to this type of OPR?</td>
<td>0.848</td>
</tr>
<tr>
<td><strong>I2P</strong> Intention to purchase (N/A)</td>
<td>Mean = 5.44, St. Dev. = 0.84</td>
</tr>
<tr>
<td>I2P If you actually had the money, how likely is it that you would buy the selected product recommended on the previous web sites?</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>PU</strong> Perceived Usefulness (Cronbach’s $\alpha = 0.804$, CoR = 0.872, AVE = 0.630)</td>
<td>Mean = 4.53, St. Dev. = 0.81</td>
</tr>
<tr>
<td>PU1 Using this type of OPR enables me to find products I want more quickly.</td>
<td>0.796</td>
</tr>
<tr>
<td>PU2 Using this type of OPR enhances my effectiveness in finding suitable products.</td>
<td>0.817</td>
</tr>
<tr>
<td>PU3 If I use this type of OPR, I will increase the quality of my judgments.</td>
<td>0.771</td>
</tr>
<tr>
<td>PU4 Using this type of OPR allows me to accomplish more analysis than would otherwise be possible.</td>
<td>0.791</td>
</tr>
<tr>
<td><strong>PEOU</strong> Perceived Ease of Use (Cronbach’s $\alpha = 0.868$, CoR = 0.910, AVE = 0.716)</td>
<td>Mean = 5.01, St. Dev. = 0.90</td>
</tr>
<tr>
<td>PEOU1 Learning to use this type of OPR would be easy for me.</td>
<td>0.837</td>
</tr>
<tr>
<td>PEOU2 My interaction with this type of OPR is clear and understandable.</td>
<td>0.844</td>
</tr>
<tr>
<td>PEOU3 It would be easy for me to become skillful at using this type of OPR.</td>
<td>0.850</td>
</tr>
<tr>
<td>PEOU4 I find this type of OPR easy to use.</td>
<td>0.853</td>
</tr>
<tr>
<td><strong>TB</strong> Trusting beliefs (Cronbach’s $\alpha = 0.926$, CoR = 0.938, AVE = 0.627)</td>
<td>Mean = 4.68, St. Dev. = 0.90</td>
</tr>
<tr>
<td>TB1 This type of OPR was competent in recommending &lt;product type&gt;.</td>
<td>0.829</td>
</tr>
<tr>
<td>TB2 This type of OPR performed its role of recommending &lt;product type&gt; very effectively.</td>
<td>0.804</td>
</tr>
<tr>
<td>TB3 Overall, this type of OPR supported me to find suitable &lt;product type&gt;.</td>
<td>0.791</td>
</tr>
<tr>
<td>TB4 I believe that this type of OPR’s dealings with me were in my best interest.</td>
<td>0.778</td>
</tr>
<tr>
<td>TB5 This type of OPR’s dealings with me felt like that it would do its best to help me.</td>
<td>0.784</td>
</tr>
<tr>
<td>TB6 I believe this type of OPR to me were truthful.</td>
<td>0.793</td>
</tr>
<tr>
<td>TB7 I would characterize this type of OPR’s dealings with me as honest.</td>
<td>0.782</td>
</tr>
<tr>
<td>TB8 This type of OPR appeared to be unbiased.</td>
<td>0.771</td>
</tr>
<tr>
<td>TB9 This type of OPR is sincere and genuine.</td>
<td>0.792</td>
</tr>
<tr>
<td><strong>PAQ</strong> Perceived Affective Quality (Cronbach’s $\alpha = 0.976$, CoR = 0.978, AVE = 0.685)</td>
<td>Mean = 4.55, St. Dev. = 1.05</td>
</tr>
<tr>
<td>Arousal quality (PAQA)</td>
<td>Sleepy quality (PAQS, reversed)</td>
</tr>
<tr>
<td>PAQA1 intense (0.859)</td>
<td>PAQS1 inactive (0.880)</td>
</tr>
<tr>
<td>PAQA2 arousing (0.842)</td>
<td>PAQS2 drowsy (0.853)</td>
</tr>
<tr>
<td>PAQA3 active (0.859)</td>
<td>PAQS3 idle (0.873)</td>
</tr>
<tr>
<td>PAQA4 alive (0.866)</td>
<td>PAQS4 lazy (0.855)</td>
</tr>
<tr>
<td>PAQA5 forceful (0.895)</td>
<td>PAQS5 slow (0.888)</td>
</tr>
<tr>
<td>Pleasant quality (PAQP)</td>
<td>Unpleasant quality (PAQU, reversed)</td>
</tr>
<tr>
<td>PAQP1 pleasant (0.861)</td>
<td>PAQU11 dissatisfying (0.834)</td>
</tr>
<tr>
<td>PAQP2 nice (0.862)</td>
<td>PAQU2 displeasing (0.831)</td>
</tr>
<tr>
<td>PAQP3 pleasing (0.860)</td>
<td>PAQU3 repulsive (0.851)</td>
</tr>
<tr>
<td>PAQP4 pretty (0.850)</td>
<td>PAQU4 unpleasant (0.925)</td>
</tr>
<tr>
<td>PAQP5 beautiful (0.847)</td>
<td>PAQU5 uncomfortable (0.923)</td>
</tr>
</tbody>
</table>

Note: CoR = Composite Reliability; AVE = Average Variance Extracted; For PAQ, standardized factor loadings are depicted in brackets right behind the indicators of the four sub-dimensions.
Table 4. Descriptives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency (%)</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td></td>
<td>Familiarity with Amazon (Likert scale 1 to 5*, Mean, StDev)</td>
</tr>
<tr>
<td>Under 20</td>
<td>35 (8.8%)</td>
<td>“Visit Amazon regularly”                                                 3.33 (0.41)</td>
</tr>
<tr>
<td>20-29</td>
<td>122 (30.8)</td>
<td>“Familiar with Amazon”                                                   4.03 (0.93)</td>
</tr>
<tr>
<td>30-39</td>
<td>132 (33.3%)</td>
<td>Internet usage and online shopping habits (Mean, StDev)</td>
</tr>
<tr>
<td>40-49</td>
<td>77 (19.4%)</td>
<td>“Internet usage hours per week”                                          15.3 (4.5)</td>
</tr>
<tr>
<td>Over 49</td>
<td>30 (7.6%)</td>
<td>“Online shopping frequency in last 6 months”                            10.4 (2.3)</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td>Household Income</td>
</tr>
<tr>
<td>Male</td>
<td>166 (41.9%)</td>
<td>Frequency (%)                10.000–19,999 Euro                                  49 (12.4%)</td>
</tr>
<tr>
<td>Female</td>
<td>230 (58.1%)</td>
<td>Under 10,000 Euro                                                       12 (3.0%)</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td>10,000–19,999 Euro                                           49 (12.4%)</td>
</tr>
<tr>
<td>Grammar/Elementary School</td>
<td>8 (2.0%)</td>
<td>20,000–29,999 Euro                                                      49 (12.4%)</td>
</tr>
<tr>
<td>High School or Equivalent</td>
<td>77 (19.4%)</td>
<td>30,000–39,999 Euro                                                      65 (16.4%)</td>
</tr>
<tr>
<td>Some College/University</td>
<td>68 (17.2%)</td>
<td>40,000–49,999 Euro                                                      73 (18.4%)</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>79 (19.9%)</td>
<td>50,000–74,999 Euro                                                      86 (21.7%)</td>
</tr>
<tr>
<td>Diploma/Master’s Degree</td>
<td>95 (24.0%)</td>
<td>75,000–99,999 Euro                                                      20 (5.1%)</td>
</tr>
<tr>
<td>Doctoral Degree</td>
<td>25 (6.4%)</td>
<td>Over 100,000 Euro                                                       8 (2.0%)</td>
</tr>
<tr>
<td>Other</td>
<td>32 (8.1%)</td>
<td>Rather not say                                                          34 (8.6%)</td>
</tr>
<tr>
<td>Rather not say</td>
<td>12 (3.0%)</td>
<td></td>
</tr>
</tbody>
</table>

Note: * anchored at (1) = strongly disagree and (5) = strongly agree

Table 5. Latent Variable Correlation Matrix

<table>
<thead>
<tr>
<th>Latent construct</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>I2R</td>
<td>(0.828)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I2P</td>
<td>0.461</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TB</td>
<td>0.587</td>
<td>0.434</td>
<td>(0.792)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU</td>
<td>0.219</td>
<td>0.195</td>
<td>-0.161</td>
<td>(0.794)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PEOU</td>
<td>0.016</td>
<td>0.086</td>
<td>-0.420</td>
<td>0.689</td>
<td>(0.846)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PAQ</td>
<td>0.571</td>
<td>0.431</td>
<td>0.478</td>
<td>-0.235</td>
<td>-0.531</td>
<td>(0.828)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OPR use</td>
<td>-0.075</td>
<td>-0.029</td>
<td>-0.557</td>
<td>0.590</td>
<td>0.742</td>
<td>-0.675</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Product Type</td>
<td>-0.134</td>
<td>-0.080</td>
<td>-0.135</td>
<td>-0.040</td>
<td>0.082</td>
<td>-0.197</td>
<td>0.005</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note: Diagonal elements in brackets are the square root of average variance extracted (AVE). These values should exceed inter-construct correlations (off-diagonal elements) for adequate discriminant validity.