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Online Recommendation Systems in a B2C E-Commerce Context: A Review and Future Directions

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Abstract

An online recommendation system (RS) involves using information technology and customer information to tailor electronic commerce interactions between a business and individual customers. Extant information systems (IS) studies on RS have approached the phenomenon from many different perspectives, and our understanding of the nature and impacts of RS is fragmented. The current study reviews and synthesizes extant empirical IS studies to provide a coherent view of research on RS and identify gaps and future directions. Specifically, we review 40 empirical studies of RS published in 31 IS journals and five IS conference proceedings between 1990 and 2013. Using a recommendation process theoretical framework, we categorize these studies in three major areas addressed by RS research: understanding consumers, delivering recommendations, and the impacts of RS. We review and synthesize the extant literature in each area and across areas. Based on the review and synthesis, we surface research gaps and provide suggestions and potential directions for future research on recommendation systems.

***Keywords**: Recommendation System, Personalization, Electronic Commerce, Consumer Preference Elicitation, Recommendation System Presentation, Recommendation System Impacts.*

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1. Introduction

Recommendation systems (RS) are used widely in many online environments, including online retailing, Internet advertisements, mobile device applications, social networks, and other major areas that involve personal transactions and communications. Amazon (www.amazon.com) is a well-known e-vendor who applies different types of RS successfully. After a consumer views or purchases an item on Amazon, the website provides the consumer with recommendations similar to the item just viewed or purchased. Further, the website provides additional recommendations in the "customer who bought this item also bought" section. These latter recommendations are based on transactional information from other consumers.

RS is a relatively new topic in information systems (IS) research. Though marketing has examined personalized services as early as 1987 (Surprenant & Solomon, 1987), it was not until the B2C e-commerce era that it became relevant to IS researchers' interests. *Communications of the ACM* published a series of papers on RS between 2000 and 2002 that provided an impetus for IS research in this area. Since then, RS has been examined through a variety of theoretical perspectives, research lenses, and empirical approaches. These different streams of research provide diverse and complementary views on RS and investigate different sets of antecedents and consequences. However, the disjointed nature of research in this area creates challenges in developing a holistic and integrated view of the phenomenon and in building a systematic cumulative research tradition. By providing an overarching research framework that integrates existing RS studies, we synthesize extant knowledge in a cohesive whole, identify what has been examined and is known, and surface gaps both in perspectives but also in the white spaces across perspectives. Through this synthesis and discussion of future directions, we hope to stimulate future research in this area in a systematic cumulative fashion.

We use Adomavicius and Tuzhilin's (2005) model of the process of providing recommendations as an overarching integrative framework to categorize extant studies into three broad areas of RS research: 1) understanding consumers, 2) delivering recommendations, and 3) recommendation system impacts. We synthesize empirical findings in each area to show the extant state of understanding on RS. Based on the review and synthesis, we surface gaps, propose new research questions and research directions, and discuss possible theoretical lenses that can be used to examine them.

2. Recommendation Systems Defined

Recommendation systems broadly refer to Web-based tools that tailor vendors' offerings to consumers according to their preferences. Review of the extant literature, however, suggests that different terms and artifacts are being used to refer to this concept. These include "personalization", "recommendation agent", "recommender", and "interactive decision aid" to name just some. Even when using the label of "recommendation system", different studies have different definitions of what such systems really are. Consequently, without a clear definition of a RS, researchers have used different manipulations when implementing a RS in their studies or have studied an assortment of different systems under the RS umbrella term.

To attain theoretical clarity, a precise definition for RS is necessary. Hence, in this section, we review different terms and definitions that have appeared in the literature. We then use the definitions to clarify the focus of our review on only studies that examine RS that provide personalized offerings. Table 1 summarizes terms that appear in prior RS literature and their definitions.

Customization, also called mass customization, refers to producing goods and services to meet individual customer's needs (Jiao & Tseng, 2001). It is a system capability that allows consumers to specify their own preferences at the latest possible point in the supply network (Chase, Aquilano, & Jacobs, 2004). Some studies in information systems examine customization systems and how they impact firms' strategies and consumers. Researchers often call a system that can provide customization services a recommendation system (Dewan, Jing, & Seidmann, 2000; Thirumalai &

Sinha, 2009). However, a customization system does not actively “recommend” anything to consumers. Rather, it provides consumers options from which to choose (e.g., Dell allows a consumer to choose a CPU model from a list of CPUs). In addition, these options are the same across all consumers—they are not personalized to individual consumers. Therefore, we do not consider customization systems as recommendation systems and, thus, do not include studies on customization in our review.

An interactive decision aid system is broader than a RS. As Häubl and Thrifts (2000) discuss, RS (which they term “recommendation agent”) is a specific type of interactive decision aid tool, which can generate personalized recommendations based on a consumer’s pre-specified preferences. Another type, which is not a RS, is the comparison matrix, which allows consumers to compare product attributes. Thus, a RS is a type of interactive decision aid system but not all interactive decision aid systems are a RS.

A personalization system is largely the same as a RS in the e-commerce environment, but not in other contexts. For example, a system can personalize a website’s attributes (e.g., font size, color, and layout style) to an individual user according to their preferences (Kumar, Smith, & Bannerjee, 2004). However, the purpose of such a system is not to recommend a vendor’s products or services to consumers. Instead, it is to increase the overall ease of use of the website. In this case, the personalization system is not a RS. In this review, we consider a personalization system to be equivalent to RS only when the system provides tailored products and services to consumers according to their preferences.

Depending on the focus of a study, a recommendation agent can refer to the same thing as a RS, or it can mean a totally different IT artifact. On one hand, a recommendation agent is defined in a few studies as a “tool to facilitate users’ decision making by providing advice on what to buy based on user-specified needs and preferences” (Wang & Benbasat, 2008, p. 249), which is close to our definition of RS. On the other hand, other studies consider recommendation agents as avatars that use animation and human voice to present recommendations (Hess, Fuller, & Campbell, 2009; Qiu & Benbasat, 2009). In order to reduce confusion, in this study, we use the most common meaning of a recommendation agent—that is, a human-like avatar that presents shopping advices (e.g., the animated gentleman in the study by Hess et al. (2009)).

In sum, we define a RS in the e-commerce context as a web-based technology that explicitly or implicitly collects a consumer’s preferences and recommends tailored e-vendors’ products or services accordingly. It is one type of interactive decision aid tool and similar to a personalization system in most contexts. A recommendation agent, in our view, is a component of a RS, which focuses specifically on RS presentation and consumer preference elicitation.

Table 1. Different Terms and Their Meanings

Terms	Definition	System's key features	System operationalization	Sample studies	Included in review?
Customization	Producing goods and services to meet individual customer's needs with near mass production efficiency (Jiao & Tseng, 2001)	Consumers proactively specify their needs. No recommendations.	Customization systems allow consumers to choose or search what they like from a pre-determined list of products (e.g., Dell.com).	Dewan et al. (2000), Thirumalai and Sinha (2009).	No.
Interactive decision aid system	An interactive tool that helps consumers to search for product information and make purchase decisions (Häubl & Trifts, 2000)	The system explicitly asks consumers for their preferences.	To elicit users' preferences, a user-aid dialogue was used to simulate the dialogues between a consumer and the decision aid system. Based on the elicited preferences, recommendations are then provided to the consumer (Wang & Benbasat 2009).	Häubl and Trifts (2000), Wang and Benbasat (2009).	Partially (include studies on a specific type of interactive decision aid—the recommendation agent).
Personalization	Personalization is the use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer (Personalization Consortium, 2003)	Provide products and services that are tailored to an individual consumer's preferences.	An example includes providing real-time weather reporting based on the customer's location and alerting the customer to serious weather conditions (Sheng, Nah, & Siau, 2008).	Tam and Ho (2005, 2006), Sheng et al. (2008), Liang, Chen, Du, Turban, & Li (2012), Lavie, Sela, Oppenheim, Inbar, & Meyer (2010), Xu, Luo, Carroll, & Rosson (2011).	Mostly (exclude studies on personalization that is not focused on recommendations).
Recommendation system	A Web-based technology that collects a consumer's preferences and recommends tailored e-vendors' products or services accordingly.	Provide product or service recommendations based on an individual consumer's preferences.	The system uses data on purchases, product ratings, and user profiles to predict which products are best suited to a particular user (Fleder & Hosanagar 2009).	Schiaffino and Amandi (2004).	Yes.
Recommendation agent	A tool to facilitate users' decision making by providing advice on what to buy based on user-specified needs and preferences (Wang & Benbasat, 2005)	User animated avatar and human voices to present recommendations.	The interface for the agent technology providing options for changing the loudness, pace, range of frequency, and word emphasis with the text-to-speech (TTS) engine and for creating agent gestures and movement (Hess et al., 2010).	Hess et al. (2009), Qiu & Benbasat (2009).	Yes.

3. Review of Prior Literature

We conducted a literature review of RS research papers published between 1990 and 2013. Since there are no clear criteria governing the choice of particular journals (Robey, Ghiyoung, & Wareham, 2008; Straub, 2006), we selected journals using a two-step approach. First, since we wanted to review literature in the IS domain, we focused on studies published in IS journals. Second, we included IS journals that either appear (a) in the Senior Scholars' basket of eight IS journals or (b) in the top 15 journals in any one of the four most recent IS journal ranking studies (Katerattanakul & Han, 2003; Lowry, Romans, & Curtis, 2004; Peffers & Ya, 2003; Rainer & Miller, 2005). This process yielded a list of 31 journals. In addition, since this research domain is relatively young, studies on this topic may appear in conference proceedings instead of journals. Therefore, we added the five most prominent conferences in information systems (i.e., ICIS, AMCIS, ECIS, PACIS, and HICSS) to our search base[1].

We identified the initial set of papers using the keywords: recommendation system, personalization, customization, interactive decision aid, recommendation agent, consumer-centric, and one-to-one marketing. We then excluded papers whose concept of RS did not match with our definition. This resulted in 90 studies on RS in 31 journals and five conference proceedings. Among these, 50 studies are conceptual papers, algorithm modeling, and general discussion notes. The remaining 41[2] are empirical studies and form the focus of this review (see Appendix A for a complete list).

4. Results

We use Adomavicius and Tuzhilin's (2005) recommendation[3] process model as the underlying framework to organize prior RS studies. Their three-stage process model suggests that the process of providing recommendations to consumers involves three basic stages: 1) understanding the consumer, which involves collecting consumer data and building consumer profiles; 2) delivering personalized recommendations, which involves matching products or services to consumer profiles, and presenting those recommendations; and 3) understanding and measuring the impacts of these recommendations and adjusting personalization strategies based on this feedback. This three-stage process model provides a comprehensive end-to-end view of the e-commerce recommendation process. It also helps us understand the extant state of knowledge and gaps both in each stage and in the white space across stages.

Figure 1 organizes prior RS studies using this framework. The left hand side of the model represents the first two stages of Adomavicius and Tuzhilin's three-stage model: 1) the process of understanding consumers and constructing consumer profiles, and 2) the matchmaking process that matches products and services to individual consumers and presents the recommendations. From a technical perspective, activities in the first two stages happen inside the "black box" of a recommendation system and are parts of the system (i.e., its algorithm and user interface). Changes in any of these affect what items are recommended to consumers and how they are presented.

Recommendation systems, whether viewed as separate components or holistically as a black box, provide personalized recommendations that vary on various attributes such as their levels of accuracy in matching consumer needs (middle box in Figure 1). These recommendations consequently impact consumer behavior and impact the organization and/or the market (the third stage of Adomavicius and Tuzhilin's process model; the rightmost box in Figure 1).

Our review follows the structure of the framework in Figure 1. We review and synthesize studies in each stage separately (Figures 2 to 5) and provide an integrated synthesis of findings across stages (Figure 6). Specifically, we review and discuss prior studies on understanding consumers in Section 4.1, on how to deliver recommendations in Section 4.2, and on recommendation system's impacts in Section 4.3. Some studies fall in more than one of these three stages. We discuss relevant aspects of these studies as appropriate for each stage.

[1] The review does not include research-in-progress papers in these conference proceedings since there was not enough information in these papers about their empirical findings.

[2] We included four papers from non-IS journals to support our discussions on a few factors and relationships.

[3] Adomavicius and Tuzhilin's (2005) use the term "personalization" process. Consistent with our earlier discussion, we use the term "recommendation" process.

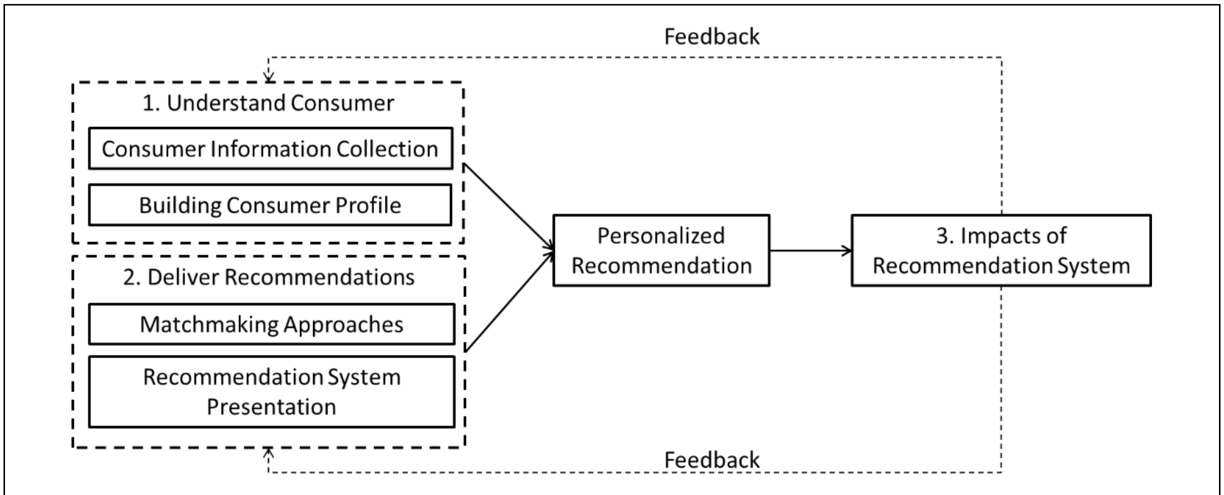

Figure 1. Three Stages of the Recommendation Process

4.1. Understand Consumers

4.1.1. Consumer Information Collection: Eliciting Consumer Preferences

In order to understand what consumers like, a recommendation system first needs to elicit and collect consumer information; then, based on this information, it estimates consumer preferences and builds consumer profiles. We identify two broad elicitation methods to collect consumer preferences: explicit and implicit. Explicit methods directly ask consumers for their preferences (e.g., sending out questionnaires), whereas implicit methods infer consumer preferences by monitoring consumers' behaviors (e.g., items viewed). In the latter case, consumers do not proactively provide information.

One common way to explicitly elicit consumer preferences is by using decision-aid tools (Wang & Benbasat, 2009). Before recommending products to a consumer, these tools usually elicit the consumer's preferences through a questionnaire. Questions may ask the purpose of buying a product, important features of the product, and price range (Qiu & Benbasat, 2009; Wang & Benbasat, 2008). Based on the consumer's responses, the decision aid will provide a set of personalized recommendations that fit with the consumer's preferences. Wang and Benbasat (2009) test three different ways, mimicking three different human decision making strategies, to explicitly collect consumers' preferences: the additive-compensatory (AC) method, the elimination by aspect method, and a hybrid method (a combination of the previous two). The AC method requires a consumer to answer attribute specific questions and indicate the importance of each attribute. The elimination method treats all attributes equally when estimating consumers' preferences. Results suggest that the AC method is perceived to be less restrictive, of higher quality, and less effortful than the elimination method, whereas the hybrid aid is not perceived to be any different from the AC method.

Systems that use implicit elicitation to estimate consumer preferences usually rely on three measures to infer preferences: click stream data of a consumer given that if a consumer clicks on a product, she must be interested in the item; the amount of time a consumer spends on a product page based on the assumption that if a consumer spends a long time viewing a product, she must be carefully examining the product, which indicates she is interested in the product; other consumers' information (e.g., who are the friends of the target consumer) on the assumption that the consumer's preferences can be influenced by or are similar to those of her friends.

Explicit and implicit methods each have distinct strengths and weaknesses. In comparing explicit and implicit methods, Liang, Lai, and Ku (2006) found that accurate recommendations are generated only when the two methods are used together. Lavie et al. (2010) corroborate these results. They found that, even though explicit methods required more effort from consumers (since consumers need to respond to preference-related questions), consumers' overall satisfaction with the system did not decrease. The cost of consumers' extra effort was compensated by the increased accuracy of recommendations (Liang et al., 2006). From a different perspective, Lee and Benbasat (2011) examined the effects of explicit and implicit methods on a consumer's perceived tradeoff difficulty in making a purchase decision. Results show that explicit methods (called weighted PEM in their study) cause stronger tradeoff difficulty than implicit methods (called cutoff PEM in the study). In addition, the negative effect of preference elicitation methods on tradeoff difficulty is greater in a loss than in a gain situation (Lee & Benbasat, 2011). Lastly, Xu et al. (2011) examined the effect of elicitation methods on consumer's privacy concern. They found that the influence of RS (labeled as personalization systems in their study) on privacy risk and on benefit beliefs vary depending on whether consumers' preferences are elicited implicitly or explicitly (they call it covert or overt). With the implicit (or covert) elicitation method, there was a significant relationship between personalization and consumers' perceived privacy risks. However, this relationship was not significant for explicit (or overt) elicitation method (Xu et al., 2011).

4.1.2. Building Consumer Profiles

Building consumer profiles refers to what information to use and how to estimate consumer preferences (Adomavicius & Tuzhilin, 2005). Consumer information can include prior product purchases and characteristics of these products, demographic information, social network information, and other consumer behaviors (e.g., clickstream data). It is not realistic, nor optimal, to use all information when building consumer profiles. Thus, e-vendors need to decide which information to include. Some e-vendors may select only a few important attributes in order to simplify the recommendation process; others may select more attributes in order to more comprehensively understand consumers. Such selective inclusion significantly affects what is recommended to consumers and, thus, affects consumers' purchase decision in later stages (Häubl & Murray, 2003).

With the widespread use of social media and social network platforms, some researchers have turned their attention to these new information sources to build consumer profiles. Gottschlich, Heimbach, and Heimbach (2013) found that, by using users' Facebook profile information, such as gender, likes, groups, posts, and geographic information, a recommendation system can yield more-accurate recommendations than just using product attributes to build consumer profiles. Park, Huh, Oh, and Han (2012) corroborate this finding. In addition, they examined the advantages of using social network information to build consumer profiles in various contexts. They found that social network-based profile building has consistently outperformed other profile-building mechanisms (e.g., profiles based on users' demographic information)[4]. Given the richness of social-network information, using such information together with traditional product attributes and consumer demographic information to accurately build consumer profiles is likely to be an increasing trend in the future.

Other than factual information (e.g., product and consumer characteristics), Adomavicius and Tuzhilin (2005) propose three techniques to build consumer profiles based on coding consumer behaviors: rules, sequences, and signatures. The rules technique views consumer profiles as a set of different attributes. For instance, "Peter reads newspaper every Monday morning" can be translated to a single rule: name = "Peter", product = "newspaper", and time = "Monday morning". In this way, a consumer's profile is a standardized set of attributes stored in a recommendation system. The sequences technique constructs consumer profiles by recording series of actions performed by a consumer. For instance, "Peter reads International news first, followed by domestic news and financial news" describes the sequence of actions when Peter reads the newspaper. Such sequence information is very useful in learning a consumer's preference priorities. The signature technique builds consumer profiles by summarizing a large amount of transactions, such as "the top five newspapers read by Peter in the last 30 days". These five newspapers will then become part of Peter's profile.

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[4] This is an emerging area as evidenced by multiple recent conference proceeding papers on the topic. The majority of these, however, are work-in-progress and do not provide sufficient empirical detail for us to include them in our review.

Summary and Future Directions

Studies on understanding consumers focus on how RS collect consumer preferences and build consumer profiles. The two major methods used to elicit consumer preferences (explicit and implicit) result in different consumer perceptions of the RS.

Results of comparative studies in consumer information collection show that explicit methods require more effort by the consumer than implicit methods, but that the former increase the accuracy of recommendations and do not raise consumers' privacy concerns (which implicit methods do). However, as Lavie et al. (2010) and Liang et al. (2006) suggest, explicit and implicit methods are complementary in that most accurate recommendations are produced when they are used jointly. Where possible, e-vendors should use both methods to elicit consumer preferences to achieve the highest level of consumer experience and the most accurate recommendations.

A boundary condition of studies in this area is that they mostly focus on one-time transactions. Explicit methods may not present the same tradeoffs in the case of multiple transactions over time (e.g., after the first visit, fewer or even no questions may be asked when a consumer visits the site). Furthermore, the frequency with which preferences are elicited may also be important in the case of longer-term relationships with a vendor involving multiple transactions. This would involve balancing the need to identify changing preferences with the cognitive effort and annoyance incurred with the frequent completion of a questionnaire. It is possible that implicit methods are a more desirable approach to elicit consumer preferences in the long run, or that a possible combination of initial explicit elicitation and ongoing implicit elicitation is a better alternative. Examining effects of explicit and implicit preference elicitation methods for long-term ongoing relationships (e.g., Amazon.com, Last.FM, etc.) and addressing some of the questions we raise above is a promising avenue for future research in this area.

There are few empirical studies on "building consumer profiles". Though Adomavicius and Tuzhilin (2005) propose several profiling techniques, we found no studies that empirically examine or compare the effectiveness of these techniques. For example, which profiling techniques more accurately estimate consumer preferences? Are they complementary or substitutive to each other? Are there any other profiling techniques? All these questions are fruitful directions for future research.

Besides product attributes and consumer behaviors, we can examine new sources of information to build consumer profiles. Currently, information used for most recommendation generation studies is limited to product attributes and consumer preferences elicited explicitly or implicitly. As much more consumer information is available online, especially unstructured information such as consumer reviews and consumer social network information (as in Gottschlich et al. (2013) and Park et al. (2012)), future studies can investigate new types of profiling approaches that use this information to build consumer profiles. For example, Malinowski, Keim, Wendt, and Weitzel (2006) propose a bilateral recommendation approach to identify people's job preferences based on information from their curriculum vitae; Shih and Liu (2005) and Hu, Zhang, Wang, and Li (2012) both propose theoretical models to elicit and match consumer preferences based on textual information (i.e., product descriptions and consumer comments). Most of these new approaches, however, have not been empirically tested for their accuracy in generating recommendations; whether or not can they provide accurate recommendations is worth investigating.

Figure 2 depicts variables and relationships that have been empirically examined in the stage of "understanding consumers" and which we discuss in this section. Table 2 summarizes all empirical studies for this stage.

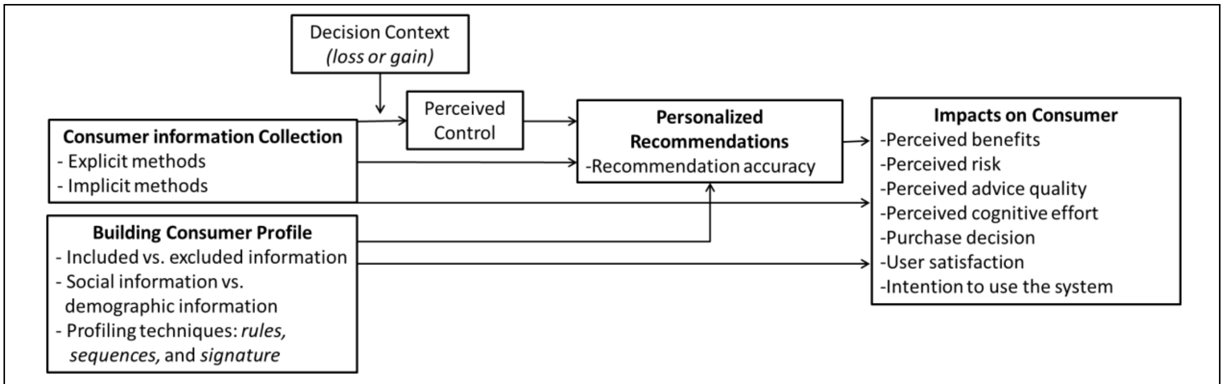

Figure 2. Relationships Investigated in the Stage of "Understanding Consumers"

4.2. Deliver Recommendations

4.2.1. Matchmaking Approaches

Matchmaking is the first step in the process of delivering recommendations to consumers (Adomavicius & Tuzhilin, 2005). The focal question to investigate in matchmaking is how we can accurately identify the products and services that match consumers' profiles as identified in the previous stage. Studies in this stream describe different types of matchmaking approaches and compare their relative accuracy.

Adomavicius and Tuzhilin (2005) identified three matchmaking approaches: content-based, collaborative-based, and hybrid. We add a fourth, newer method: the social network-based recommendation approach. Each matchmaking approach can use explicit methods, implicit methods, or a combination of both methods to collect consumer information. However, the matchmaking approach used is tightly connected to the type of information the recommendation system uses to construct consumer profiles. In the next few paragraphs, we briefly describe these approaches and how they work in the online e-commerce context. The content-based approach recommends services or products similar to the ones the consumer preferred in the past (Adomavicius & Tuzhilin, 2005). By design, content-based approach relies heavily on consumers' historical transactions. Since consumers' transaction information is easy to collect and use, this type of matchmaking approach is the most widely adopted approach today.

Table 2. Empirical Studies on Understanding Consumers

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
Customer information collection methods				
Lavie et al. (2010)	Implicit and explicit methods of generating user profile	The match with user interests (recommendation accuracy)	Breadth and depth of personalization	Both explicit and implicit elicitation methods are helpful in estimating user preferences. To have the highest accuracy, it is better to have implicit and explicit methods combined, so that users are still involved in the creation of their profile but do not have to invest much effort into it.
Lee & Benbasat (2011)	Implicit and explicit methods of preference elicitation	Tradeoff difficulty, perceived control, perceived recommendation accuracy, intention to use recommendation system	Concepts related to cognitive tradeoff and perceived control	The decision context (loss or gain) moderates the degree to which that preference elicitation method (explicit or implicit) generates tradeoff difficulty. Tradeoff difficulty influences users' evaluations of a recommendation agent via perceived control.
Liang et al. (2006)	Explicit vs. Implicit methods of generating user profile (termed explicit/implicit user feedback), individual motivation	Recommendation accuracy, user satisfaction	Effort-based theories, motivation-based theories, process-oriented theory	Explicit and implicit methods have similar effects on overall user satisfaction with the recommendation system and recommendation accuracy.
Customer profile building and impacts				
Gottschlich et al. (2013)	User profiles (gender, likes, groups, hometown, and posts)	Users' taste (recommendation accuracy) and purchase intention	Consumer profile building and matchmaking	Using Facebook user profile information (such as liked music, brands, and product information) yields significantly better recommendations than a pure random draw from the product database.
Häubl and Murray (2003)	Included and excluded primary product attributes	Consumer purchase decision	Consumer preference construction	Everything else being equal, the inclusion of an attribute in a recommendation agent renders this attribute more prominent in consumers' purchase decisions.
Park et al. (2012)	User profiles (demographic information vs. social network information)	Prediction accuracy (accuracy of consumer profile estimation)	Data validation and network theories	When building consumer profiles, the social network-based inference model consistently outperforms other competing mechanisms regardless of the criteria choice.
Xu et al. (2011)	Overt vs. covert personalization	Perceived benefits of information disclosure; perceived risks of information disclosure.	Privacy calculus	Personalization system, which uses covert elicitation methods, has a significant effect on user's perceived privacy risk. The relationship is not significant when the personalization system uses overt elicitation method.
Wang & Benbasat (2009)	Explanation facilities; decision strategy (different methods of explicitly collecting consumer preferences)	Perceived advice quality; perceived cognitive effort	Decision related theories	The additive-compensatory (AC) aid is perceived to be less restrictive, of higher quality, and less effortful than the elimination aid, whereas the hybrid aid is not perceived to be any different from the AC aid.

Though widely adopted and easy to implement, content-based matchmaking has three major shortcomings: shallow analysis, over-specification, and eliciting user feedback (Bakabanovic & Shoham, 1997). Shallow analysis suggests that analysis by this approach is based on limited information. In other words, this approach typically uses only historical rating, viewing, and purchases to construct consumer profiles. Aesthetic quality and multimedia information are ignored (e.g., current content-based RS are not able to analyze aesthetic features of products and, thus, these features are ignored). Over-specification means that the system will only recommended items that are similar to what a customer has already rated, viewed, or purchased. As a result, recommendations are limited to a specific range of items and do not expose the customer to a broader set. Eliciting user feedback refers to the fact that the recommendation quality can only be improved if the user provides additional ratings on products or purchases/views additional products (Bakabanovic & Shoham, 1997).

The collaborative approach, also known as collaborative filtering, recommends items to the consumer that people with similar tastes and preferences have liked in the past (Adomavicius & Tuzhilin, 2005). The recommendation system supporting the “consumer who bought this item also bought” feature on Amazon is a typical example of this approach. Since the collaborative approach is based on a much larger pool of user ratings and purchases, it addresses most of the shortcomings of the content-based matchmaking approach. However, because it performs no or limited analysis on product attributes, this approach has its own shortcomings: lagged new item recommendation and poor recommendation quality for unusual users (Bakabanovic & Shoham, 1997). A new item will not be recommended to a consumer until “more information about it is obtained through another user either rating it or specifying which other items it is similar to” (Bakabanovic & Shoham, 1997, p. 67). In addition, a consumer with idiosyncratic tastes may have no peers at all. In this case, there is no way to match this consumer’s tastes with others and to provide collaborative recommendations.

With the proliferation of social network information, RS can also use social network data as a new source of information in building consumer profiles (Arazy, Kumar, & Shapira, 2010). In fact, Amazon has already introduced an application called “Your Amazon Facebook Page”, which provides recommendations based on prior purchases by consumers’ friends on Facebook. The presumption for this type of matchmaking approach is that consumers have similar preferences (i.e., profiles) as their friends because of social influences among consumers. This new matchmaking approach opens up a whole new avenue of research in recommendation systems.

The hybrid approach combines two or more of the above matchmaking approaches. Burke (2002) proposes seven different methods, with various weighting techniques, to perform hybrid matchmaking. Since the hybrid approach combines multiple approaches, it requires more effort and a larger information base to support it. Though e-vendors need to know whether the hybrid approach can indeed perform better (e.g., in terms of higher user satisfaction, higher recommendation accuracy, or less consumer cognitive effort) than any of the individual matchmaking approaches, how the seven hybrid methods differ on their impacts on consumers is still an open question.

Recommendation Accuracy

The ultimate objective of matchmaking is recommendation accuracy. Recommendation accuracy generally refers to the degree to which personalized recommendations match with the focal consumer’s preferences (Ho, Zhang, & Wang, 2011; Li & Karahanna, 2012; Ochi, Rao, Takayama, & Nass, 2010). Providing accurate recommendations is the desired output of any RS and the foundation of RS’s various impacts. As such, recommendation accuracy is a core dependent variable for empirical studies on matchmaking approaches. As Table 3 shows, prior studies have used both subjective and objective methods to measure recommendation accuracy. Subjective measures focus on consumers’ evaluations of the personalized recommendations. After personalized recommendations are generated, consumers respond to questions such as: “the personalized recommendations include items that match what I am looking for” and “how likely are you to try this [personalized recommendation]” (Ho et al., 2011, p. 669; Li & Karahanna, 2012, p. 738). Objective measures are based on click streams on recommended offerings such as the number of total clicks on the recommended items divided by the total number of recommendations (termed “precision” by

Liang et al. (2006) and "prediction accuracy" by Sahoo, Singh, and Mukhopadhyay (2012)). Both subjective and objective measures are good proxies for recommendation accuracy.

Determining which recommendation generation approach provides the highest level of accuracy under what conditions is still an open question. Only a few studies compare the relative recommendation accuracy of different matchmaking approaches. Ochi et al. (2010) report that product type moderates the accuracy of different matchmaking approaches. They found that, compared to the collaborative approach, the content-based approach generated more-accurate recommendations for search products, but that, when providing recommendations for experience products, the collaborative approach was more accurate. By comparing different collaborative filtering algorithms, Sahoo et al. (2012) found that a new collaborative filtering algorithm, based on Hidden Markov Model (HMM), outperformed traditional collaborative filtering techniques, especially when consumers' preferences are changing. Li and Karahanna (2012) compare the collaborative and the newer social network-based matchmaking approaches. They examine recommendation accuracy under two different conditions: 1) in the focal category based on which collaborative peers were identified (e.g., focal consumer and peers all like the same books; then the accuracy of book recommendations are evaluated), and 2) across different categories (e.g., focal consumer and peers all like the same books; then the accuracy of movies, music, and restaurants recommendations are evaluated). Their findings suggest that the social network-based approach provides more accurate recommendations than the collaborative approach when recommendations are not in the same category (the second condition). The two approaches have the same level of accuracy when recommendations and preferred products are in the same category (the first condition).

Finally, since the hybrid approach combines different approaches, we would expect that it can overcome the weaknesses of using a single recommendation approach. Xiao and Benbasat (2007), relying on trust theories and the technology acceptance model (TAM), propose that the hybrid approach will lead to "greater trust, perceived usefulness, and satisfaction but to lower perceived ease of use" (p. 161). However, this theoretical claim has not yet been examined empirically.

Other than comparing the four approaches mentioned above, another interesting lens would be to examine the relative efficacy of dynamic versus static matchmaking processes. Ho et al. (2011) compare the relative recommendation accuracy between an adaptive matchmaking approach, which updates consumers' preference profiles in real time as consumers make purchase, and a static approach, which does not. In multiple contexts, they found that the adaptive approach was more accurate than the static approach.

A noteworthy finding of our review of matchmaking approaches is that most extant studies on RS do not explicitly specify which type of matchmaking approach they use. This is important to the extent to which findings from one type of approach do not generalize across approaches. In some studies, we can infer the approach used to generate recommendations from the description of the research design. Table 4 presents the empirical studies that have clearly stated how they generate recommendations and, thus, we can infer the type of matchmaking approach used.

The table reveals that the majority of the extant RS research have focused on the content-based approach, while very little research attention has been devoted to collaborative, hybrid, or social network-based approaches. This may be due to the fact that the content-based recommendation generation approach is easier to implement, especially in experimental settings that use student subjects where one can more quickly and easily elicit preferences based on each subject's behavior. One may argue that findings from one matchmaking approach can generalize to all three types. However, such generalizability depends on the whether the research focuses on approach-specific information or not. When we do not view the RS as a black box (i.e., when we go beyond viewing the RS as the presence or absence of recommendations) and we are interested in analyzing approach-specific characteristics, we have to specify which recommendation generation approach is used. This will help us understand the context to which results can be generalized.

Table 3. Definitions and Measures of Recommendation Accuracy

Paper	Definition	Measurement items
Ho et al. (2011)	The degree to which a recommended item matches with a consumer's preference.	The personalized recommendations include items that match what I am looking for; the personalized recommendations include items that I like.
Lavie et al. (2010)	The degree to which the personalized recommendations are relevant to a user's preferences.	To what degree do you think these items are relevant to your personal fields of interest?
Liang et al. (2006)	The ability of the personalized method to capture audience interest.	Precision: the portion of recommended news that is relevant (i.e., number of recommended and read/number of recommended). Recall: the portion of relevant news that is recommended (number of recommended and read/total number read).
Li & Karahanna (2012)	The extent to which a given recommendation matches a focal consumer's preferences.	How likely are you to try this [personalized recommendation]?
Ochi et al. (2010)	The degree to which the generated recommendations match a user's preferences.	How much would you like this [recommended product]?
Sahoo et al. (2012)	The degree to which the collaborative filtering provides accurate recommendations.	Prediction accuracy: the probability that recommended items are observed by users.
Tam & Ho (2005, 2006)	The extent to which the Web content generated by the personalization agent appeals to users.	Presence of personalized recommendations: personalized recommendations = 1; random offerings = 0.

Figure 3 depicts variables and relationships examined in prior studies in matchmaking approaches and their effects.

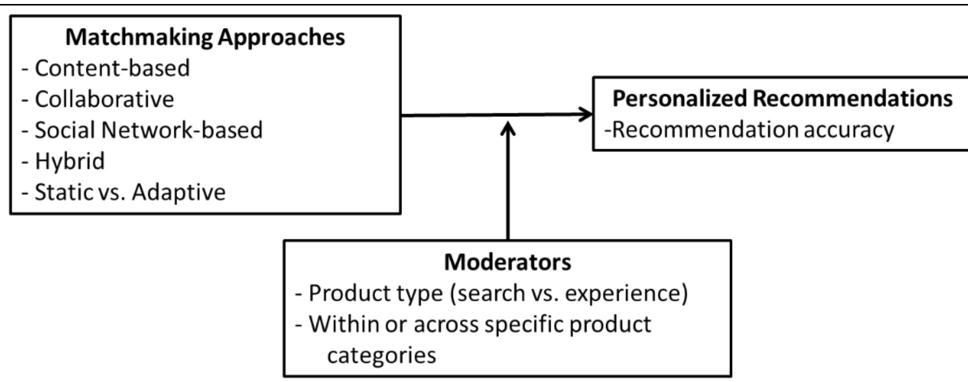

Figure 3. Relationships Investigated in Matchmaking Approaches

Summary and Future Directions

Research on matchmaking focuses on generating accurate recommendations using different matchmaking approaches (content-based, collaborative, social network-based, and hybrid). It presents a minority of the empirical studies on RS. Results suggest that different types of matchmaking approaches have varying levels of accuracy in generating recommendations under different conditions. Table 5 summarizes the three empirical studies on the topic. Two promising research directions on matchmaking approaches emerge: improvement of a single approach and comparison across different approaches.

In studying a single matchmaking approach, the primary focus is on improving the existing algorithm and matchmaking process. Although quite a few algorithm, process design, and modeling studies in this area exist (e.g., Miller, Resnick, & Zeckhauser, 2005; Mobasher, Cooley, & Srivastava, 2000; Sackmann, Struker, & Accorsi, 2006), few empirical studies test the proposed algorithms and models using real-world data. To impact practice, it would be beneficial to empirically test the proposed algorithms, processes, and models of matchmaking in an e-commerce environment and examine their practical value.

Given that implementing these matchmaking approaches requires monetary investments by the e-vendors, comparisons among different types of matchmaking approaches can be helpful in examining the relative efficacy of these approaches under many contingency conditions. However, few studies have systematically compared and contrasted effects of different types of RS on recommendation accuracy and on consumer outcomes. As such, which matchmaking approach provides higher recommendation accuracy under what conditions is still an open question.

Furthermore, it is important to determine the conditions under which different matchmaking approaches can generate accurate recommendations. Extant research has examined the type of product (search vs. experience) (Ochi et al., 2010) and whether recommendations are inside vs. outside the focal product category (Li & Karahanna, 2012). Future research can systematically examine additional factors that can affect matchmaking approaches' accuracy. The answers to this question would enable e-vendors to make an informed choice of matchmaking approaches.

Table 4. Summary of Matchmaking Approaches Used in Prior Studies

Matchmaking approach	Papers	Consumer information source
Content-based	**(16 papers in total)** Al-Natour, Benbasat, & Cenfetelli (2006), Brynjolfsson, Smith, & Yu (2003), Greer & Murtaza (2003), Hinz, Eckert, & Skiera (2011), Komiak & Benbasat (2006), Lavie et al. (2010), Liang et al. (2006), Liang et al. (2012), Ochi et al. (2010), Qiu & Benbasat (2009), Tam & Ho (2005), Tam & Ho (2006), Wang & Benbasat (2005, 2007, 2009), Xu et al. (2011)	Consumer historical data, which include: previous purchases, ratings, and other behaviors (e.g., scrolling, browsing time on a product).
Collaborative	**(5 papers in total)** Greer & Murtaza (2003), Fleder & Hosanagar (2009), Sahoo et al. (2012), Oestreicher-Singer & Sundararajan (2012a), Ochi et al. (2010)	Preferences of other consumers with similar purchases and purchase patterns.
Social network-based	**(2 papers in total)** Arazy et al. (2010), Li & Karahanna (2012)	Consumer's social network information, which include: tie strengths, preferences of consumers with high homophily.
Hybrid	**(2 papers in total)** Shih & Liu (2005), Kumar & Benbasat 2006)	Combinations of content-based and collaborative information.

Table 5. Empirical Studies Comparing Matchmaking Approaches

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
Ho et al. (2011)	Recommendation approach (adaptive vs. static), time of presenting recommendation (early or late)	Consumer satisfaction, quality of recommendations (i.e., accuracy)	Consumer search theory, stopping rule model	Recommendation quality improves over the course of an online session, but the probability of considering and accepting a given recommendation diminishes over the course of the session. Adaptive recommendations are always better than static recommendations.
Li & Karahanna (2012)	Recommendation approach (social network-based vs. collaborative), product category	Recommendation accuracy	Social influence theories; homophily theory	Social network-based approach can provide as accurate recommendations as those of the collaborative approach when within a specific product category and better than the collaborative approach when outside the specific category.
Ochi et al. (2010)	Recommendation approach (content-based vs. collaborative), product type (experience vs. search products)	Liking of the recommendations (recommendation accuracy), user positive feelings	Recommendation algorithms	For experience products, both content-based and collaborative recommendations have similar levels of accuracy; however, for search products, in general, collaborative recommendations have a higher level of accuracy than content-based recommendations.
Sahoo et al. (2012)	Different types of collaborative filtering matchmaking approaches	Recommendation accuracy	Collaborative filtering based on Markov model	Hidden Markov model (HMM) based collaborative filtering performs and the best of others in normal conditions. HMM does a much better job of tracking the users' changing preferences through the test period than static collaborative filtering approaches.

4.2.2 Recommendation System Presentation

Once recommendations are generated based on the matchmaking process, the next step in the process of "delivering recommendations" is to present these recommendations to consumers (Adomavicius & Tuzhilin, 2005). A central focus for this step is designing a good system interface to present the recommendations. Without careful interface design, consumers may ignore the personalized recommendations, take a lot of time to understand what was offered, or not perceive them as personalized recommendations at all. Thus, one main goal of RS interface design is to persuade consumers to adopt the personalized recommendations by facilitating their decision making process; that is, by making it easier and less effortful to identify and select products or services that match their preferences. Clearly, recommendations will not aid decision making if consumers do not perceive them to be "good" recommendations worthy of consideration and/or adoption. Studies in this stream focus on three broad areas to examine the efficacy of interface design to present recommendations: 1) consumer decision process, 2) direct impacts on consumer perceptions, and 3) mediated impacts via social presence on consumer trust. Next, we organize our review of RS presentation using these three categories.

Recommendation Presentation and Its Effect on the Decision Making Process

Given that an objective of RS is to persuade consumers to purchase the recommended products, theories of persuasion have been used to inform how user interface features in presenting RS recommendations influence the consumer's decision making process. For example, Tam and Ho (2005) use the elaboration likelihood model of persuasion (ELM) (Petty & Cacioppo, 1986) to examine how sorting cue (a number indicating how well a recommended item matches the consumer's preferences) and recommendation set size (the number of recommendations shown on a single page) influence consumer's adoption of recommendations. They examined effects on two outcomes reflecting two stages of the decision process: whether the recommendation receives attention, and whether it is accepted by the consumer. They found that presence of sorting cues and a large set of recommendations are more likely to catch consumers' attention as compared to a small set of recommendations without sorting cues. However, acceptance of recommendations was determined by the extent to which the recommendations matched the consumer's preferences (i.e., recommendation accuracy) and by the presence of sorting cues.

Though there are very few studies in this area, using theories of persuasion and decision making to identify user interface features that can direct consumers' attention to recommendations and influence their decision making process is a promising avenue for future research. Besides ELM, other theories related to decision making or persuasion such as human information processing (Newell & Simon, 1972; Tversky & Kahneman, 1981), attention (Knudsen, 2007; Treisman & Gelade, 1980), and different decision strategies (Creyer, Bettman, & Payne, 1990; Johnson & Payne, 1985; Payne, Bettman, & Schkade, 1993) may prove useful in identifying important recommendation presentation features and in theorizing their effect on the consumers' decision making process.

RS Presentation and Its Direct Effects on Consumers' Perceptions

The extant literature on RS has examined the effects of different RS presentation features, such as recommendation guidance, directions, and explanation facilities, on perceived similarity in personality and behavior (Al-Natour et al., 2006) and trust beliefs (Wang & Benbasat, 2005, 2007, 2008). Suggestive guidance and explanation facilities present recommendations along with explanations as to why those recommendations are provided to consumers. Al-Natour et al. (2006) found that the presence of suggestive guidance, similar to the explanation facility in Wang and Benbasat's studies, influenced consumers' perceived similarity between themselves and the RS (i.e., the extent to which the presented clues match with focal consumer's personality and decision strategy). According to the similarity attraction theory (Byrne, Griffitt, & Stefaniak, 1967), consumers are more likely to trust a system they perceives as being similar to them (Al-Natour et al., 2006), and, thus, more likely to adopt the recommendations.

In addition to mediated effects through perceived similarity, explanation facilities also have direct impacts on consumers' trust beliefs. Wang and Benbasat (2005, 2007, 2008) conducted a series of studies on how explanation facilities can increase a consumer's trust in recommendation systems. They categorize three types of explanations: how, which explain how recommendations are generated; why, which justify different importance levels of product attributes used in generating recommendations; and trade-off, which help users make trade-offs among different attributes (Wang & Benbasat, 2007). By providing these explanations, they found that a consumer's overall trust in the recommendation agent increased significantly (Wang & Benbasat, 2008). Specifically, how explanations increased consumers' competence and benevolence trust beliefs, why explanations increase consumers' benevolence trust beliefs, and trade-off explanations increase consumers' integrity beliefs (Wang & Benbasat, 2007).

RS Presentation and the Mediating Effect of Social Presence

Given that trust in its recommendations is important for consumers to adopt a RS, to increase a consumer's trust in personalized recommendations, the RS's social presence has emerged as an important factor (Hess et al., 2009; Kumar & Benbasat, 2006; Qiu & Benbasat, 2009). This is especially so when recommendations are presented by a recommendation agent such as an avatar (e.g., an animated persona). Social presence refers to the degree to which a medium allows an individual to establish a personal connection with others (Short, Wiliams, & Christie, 1976) and is positively related to system perceptions such as perceived usefulness (Karahanna & Straub, 1999) and trust *(*Gefen & Straub, 2003; Hassanein & Head, 2005). As such, social presence has been posited as an important mediator between RS presentation and consumer trust beliefs and other consumer perceptions of RS such as perceived usefulness and perceived enjoyment (Qiu & Benbasat, 2009; Wang & Benbasat, 2005).

Studies in this vein focus on how to increase the RS's social presence by manipulating various interface design factors. For example, Qiu and Benbasat (2009) found that, when the RS embedded human voice (versus pure text) and humanoid embodiment (as in the case of an avatar), consumers' perceived social presence increased. This leads to a higher trusting belief and perceived enjoyment (which is a social benefit that consumers perceive when interacting with a recommendation agent) (Qiu & Benbasat, 2009). In addition, focusing on recommendation agents (i.e., avatars), Hess et al. (2009) identified two other presentation factors that can influence social presence directly or indirectly: a recommendation agent's extraversion and interface vividness. Consumers treat recommendation agent's extraversion as a key social technology cue positively influencing consumer perceptions social presence. This positive relationship is strengthened by interface vividness (Hess et al., 2009).

Summary and Future Directions

To present personalized recommendations, a personalization system's interface should be easy to use, present the recommendations in a manner that attract attention, be able to enhance the recommendation agent's social presence (if the system uses a recommendation agent), instill trust in the recommendations, and be able to help a consumer in making better purchase decisions. Figure 4 presents the variables and relationships on RS presentation that prior research has examined.

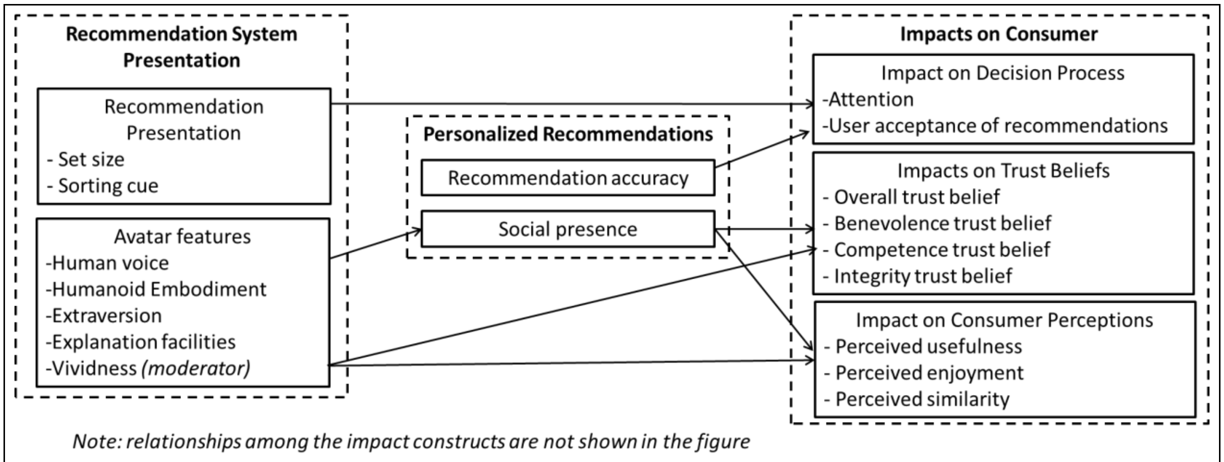

Figure 4. Relationships Investigated in RS Presentation

Table 6 summarizes different presentation features of RS that have been investigated in prior studies. As we can see, few presentation (interface design) features have been examined in the extant RS literature. Furthermore, except for the case of avatars where research has focused on ways in which to enhance social presence, there has been little systematic research on how to present personalized recommendations to consumers. We have already discussed using theories of persuasion, information processing, and attention in deriving theory-based approaches to presentation. The comprehensive framework for human computer interaction (HCI) studies outlined by ACM-SIGCHI (2009) may also be used to guide studies on RS presentation. The framework includes four major aspects of HCI: use and context (how and where the system is used), human (users of the system, including human information processing and language, communication and interaction), computer (system artifacts including dialog techniques, dialogue genre, dialog architecture, input & output devices, and computer graphics), and development process (how the system is developed and evolved). Most existing studies on RS presentation fall in two particular categories of the framework: the dialogue techniques, which relate to output techniques, and screen layout issues, and the dialogue genre, which includes interaction metaphor designs (e.g., avatars used in RS). Other than these, other HCI areas have received less attention and may provide interesting directions for future research.

Table 6. RS Presentation Features Investigated in Prior Studies

Study	Interface features
Interface features	
Tam & Ho (2005)	Recommendations set size (the number of recommended products)
	Recommendations sorting cue (ranking based on preference match)
Avatar features	
Hess et al. (2009)	Recommendation agent's vividness (text, voice, and animation)
	Recommendation agent's extraversion (e.g., voice pitch, volume, animation gesture)
Al-Natour et al. (2006)	Text
	Voice
	Avatar appearance
Qiu & Benbasat (2009)	Humanoid embodiment (avatar vs. none)
	Output modality (human voice vs. text-to-speech vs. text)
Wang & Benbasat (2005, 2007, 2008)	Explanation facilities:
	Why: justify the importance and purpose of attributes and provided recommendations.
	How: reveal the line of reasoning used by an RA based on consumer needs and product attributes preferences.
	Guidance/trade-off: help users to make trade-offs among product attribute preferences

For instance, on the human side, since consumer's preferences can be constructed during the online shopping process (Bettman, Luce, & Payne, 1998; Häubl & Murray, 2003), future research could focus on different RS interface design and cues to guide and affect consumers' information processing and decision making. In addition, given that webpage visual design affects user's feelings and emotions (Deng & Poole, 2010) and that emotion can influence user's decisions (Han, Lerner, & Keltner, 2007), research on RS interface design can examine how to influence consumer's emotion.

In terms of communication and interaction, perceived control, discussed in the stage of eliciting consumer information (Lee & Benbasat, 2011), can be an important factor when delivering recommendations. Research shows that, when a system enables consumer control over their interaction with the system, consumers perceive the information provided by the system to be more valuable. The information, as a result, will have a higher impact on consumer's decision and judgment (Ariely, 2000). Thus, designing how to embed control mechanisms in a RS, such as allowing consumers to control which matchmaking approach to use or how many recommendations to present in the result list, and examining how these controls affect consumer decisions and attitudes towards RS are good directions for future research. Table 7 summarizes existing studies in this area.

Table 7. Empirical Studies on RS Presentation

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
To affect decision process				
Tam & Ho (2005)	Level of preference matching, recommendation set size, sorting cue	Cognitive effort in decision making, user acceptance of personalized recommendations	Elaboration likelihood model	Recommendation accuracy (the level of preference matching) is a key factor to influence users' choice of personalized recommendations. Larger recommendation size and sorting cue can attract users' attentions to a greater extent.
To affect trust beliefs and consumer perceptions (including social presence)				
Al-Natour et al. (2006)	Recommendation agent's suggestive guidance, directives, and decision rules	Perceived personality; perceived similarity (personality and behavioral)	Similarity-attraction theories	Design characteristics can be used to manifest desired personalities and behaviors in a recommendation agent, and, thus, create matching perceptions of personality and behavioral similarity between customer and the system.
Hess et al. (2009)	Recommendation agent's extraversion, interface vividness, computer playfulness	Social presence, trusting beliefs	Social presence theories, trust theories	RA extraversion and computer playfulness positively influence perceptions of social presence. Interface vividness has a positive, direct effect on social presence and it moderates (strengthens) the effect of RA extraversion on social presence.
Qiu & Benbasat (2009)	Humanoid embodiment and output modality (human voice vs. text)	Social presence, trusting beliefs, perceived usefulness, perceived enjoyment, usage intention	Social agency theory, trust theories, and technology acceptance model	Using humanoid embodiment and human voice-based communication significantly influences users' perceptions of social presence, which, in turn, enhances users' trusting beliefs, perceptions of enjoyment, and, ultimately, their intentions to use the agent as a decision aid.
Wang & Benbasat (2005)	Types of explanation facilities (how, why, and guidance), perceived ease of use of a recommendation agent	Perceived usefulness, trust, intention to use	Technology acceptance model, trust theory	Explanation facilities enhance users' trust in recommendation agent. This leads to higher levels of perceived usefulness and intention to adopt online the recommendation agent.
Wang and Benbasat (2007)	Explanation facilities (how, why, and trade-off)	Competence trust belief, Benevolence trust belief, Integrity trust belief	Trust theories	The results confirm the important role of explanation facilities in enhancing consumers' initial trusting beliefs and indicate that consumers' use of different types of explanations enhances different trusting beliefs
Wang & Benbasat (2008)	Types of explanation facilities (how, why, and guidance), reasons for using a recommendation agent	Trust in recommendation agent	Trust theories, trust reason literature	Explanation facilities can significantly increase a user's trust in the recommendation agent.

4.3. Recommendation System Impacts

Studies on how personalized recommendations impact consumers focus on how RS change a consumer's beliefs and behaviors in various contexts. This area of research has received the most attention in the literature. Though we have mentioned some RS impacts in the previous sections, we here review additional studies in this area that consider RS as a single black-box factor (that is, whether the RS exists or not) regardless of preference elicitation method, consumer profile building, recommendation matchmaking, or RS presentation features. In reviewing these studies, we conclude that only a limited number of theoretical perspectives have been applied to examine this area. These include the technology acceptance model (TAM) (Davis, 1989), the theory of reasoned action (TRA) (Fishbein, 1979), information privacy related theories (Malhotra et al., 2004), and trust theories (Gefen et al., 2003). Switching cost theories (Klemperer, 1987), transaction cost theory (Liang et al. 2012) and some other theories also appear in these studies but only once or twice. In the following two sections, we discuss the impacts on individual consumers and impacts on the market as a whole respectively.

4.3.1. Impacts on Consumer

Impacts on consumer refer to the personalized recommendations' effects on a) a consumer's perceptions (e.g., perceived usefulness) and intentions, and b) on a consumer's decision making process of making a product selection or purchase.

Many studies in the former category rely on TAM and TRA to show that recommendations increase consumers' perceived usefulness (Chau & Lai, 2003; Kumar & Benbasat, 2006; Liang et al., 2012), perceived benefits (Chau & Ho, 2008), and positive attitude toward the system (Chau & Ho, 2008; Chau & Lai, 2003; Xu, 2006). These effects may be direct (e.g., Chau & Lai, 2003, Kumar & Benbasat 2006) or mediated by other variables such as transaction costs and perceived care (Liang et al., 2012). For example, Liang et al. (2012) found that the presence of personalized recommendations significantly increased consumers' perceived care and reduced consumers' time and effort (i.e., transaction costs) in searching for products, which increased perceptions of usefulness. When consumers perceive the RS to be useful and have positive attitudes towards it, they are more likely to use it (Greer & Murtaza, 2003; Thongpapanl & Ashraf, 2011). Another important consumer perception discussed in the literature is privacy concerns (Awad & Krishnan, 2006; Sheng et al., 2008). Based on consumer utility maximization theory and privacy calculus (Dinev & Hart, 2006), consumers weigh the benefits of using RS against the negative consequences of releasing personal information. If the negative consequences outweigh the benefits, consumers are less likely to use RS.

In addition, studies that focus on recommendation agents examine effects on trust beliefs. For example, Komiak and Benbasat (2006) found that perceived personalization had significant direct effects on cognitive trust and indirect effects on emotional trust, and that the two types of trust further influenced consumers' intention to adopt a recommendation agent. Further, Wang and Benbasat (2008) identify six antecedents of trust to a recommendation agent (i.e. dispositional, institutional, heuristic, calculative, interactive, and knowledge-based), especially at the trust-forming stage.

Other studies have focused on the effect of RS on consumers' decision making process. Users are more satisfied with the recommendations and more likely to accept them if the personalized recommendations are presented at the early stage of an online session (Ho et al., 2011). That is, the timing of offering personalized recommendations matters. Further, building on social cognition theories (Wyer & Srull, 1989) and human information processing in decision making (Huber & Seiser, 2001), Tam and Ho (2006) examined the effect of recommendations on all four decision stages (attention, cognitive processing, decision, and evaluation) of purchasing a product. They found that the presence of personalized offerings and content relevance of recommendations (i.e., *recommendation accuracy*) significantly affected consumers' cognitions and perceptions in all four decision stages. In particular, personalized recommendations were perceived by consumers as more useful than random offerings and they reduced consumers' cognitive load in making a purchase decision. Häubl and Trifts (2000) present similar findings on the RS's effects on a consumer's cognitive effort and decision quality. They found that, in the presence of RS (termed recommendation agent in their study), the number of products a consumer considers and the amount of product search involved reduced significantly (i.e., a consumer's cognitive effort is reduced) while their decision quality and their confidence in the purchase decision increases significantly, which indicates that the RS can help consumers make better decisions.

4.3.2. Impacts on Market

RS impacts have also been examined at the market level. Though few studies exist at this level, they yield inconsistent findings and there is a debate in the literature about the nature of these effects. A focus of this debate has been on whether RS homogenize or heterogenize consumer preferences (in terms of sales diversity). One view is that personalized recommendations by an e-vendor limit consumers' ability to explore a variety of products and services (Pariser, 2011). Two studies empirically tested this idea and found that product sales became increasingly more homogenized and more narrowly focused because only similar and popular products were recommended to consumers (Fleder & Hosanagar, 2009; Oestreicher-Singer & Sundararajan, 2012a). An alternative view is that RS, in fact, diversifies product sales. The argument supporting this view suggests that recommendations systems increase the exposure of unpopular products that consumers may have previously ignored. By recommending a variety of products (both popular and unpopular) to consumers, RS heterogenizes sales across a variety of products (Brynjolfsson, Hu, & Simester, 2011; Hinz et al., 2011). Both sides of the debate have merit and provide empirical evidence to support their assertions. An interesting observation about the debate is that, apparently, both sides do not consider possible variations inside the RS "black box"—they do not consider the recommendation matchmaking approach used in their study (except for Fleder and Hosanagar's work in 2009, in which they explicitly mention that they examined a collaborative filtering RS in their study), nor examine the accuracy of their personalized recommendations. Based on our previous discussion, there are many factors in a RS "black box" that can affect recommendations' impacts. Future studies can examine the homogenizing or heterogenizing effects by bringing these factors into consideration. Only then will we have a better understanding on personalization's impacts on product sales and consumer preferences at the market level. A study by Oestreicher-Singer and Sundararajan (2012b) found an interesting "side effect" of using recommendation systems: as products are directly linked via hyperlinks or indirectly linked via a common platform (e.g., Amazon.com), products form a network as well. Due to these network relations, a RS will not only increase the sales of recommended products, but also the sales of connected products (termed complementary products). This provides a new perspective to examine the effects of RS on the market by expanding these effects beyond the products the RS recommends and examining diffusion effects to other products via the product network.

Summary and Future Directions

The impacts of RS on consumers focus on two sets of variables: those relating to the impact of RS on the decision making process of making a product selection or purchase, and those that reflect perceptions of RS and intentions to use it in the future. This area has received much more research attention compared to the other areas. Studies have used a narrow set of well-established theories (i.e., TAM and trust theories), and have examined impact on consumer's perceptions of usefulness, trust, privacy concerns, attitude, and usage. By and large, results support that RS enhance consumer perceptions of usefulness, promote positive attitudes, and lead to higher use intentions. Findings also suggest that perceived personalization instills trust, and consumers trade away privacy concerns for the personalization benefits that come from using these systems. Furthermore, RS has a positive effect on the consumer decision making process by reducing cognitive effort and increasing decision quality and confidence in their decisions. At the market level, the findings on RS's effects are inconsistent. Such inconsistency could be due the variations in RS itself. Figure 5 shows the variables and relationships examined in this research area.

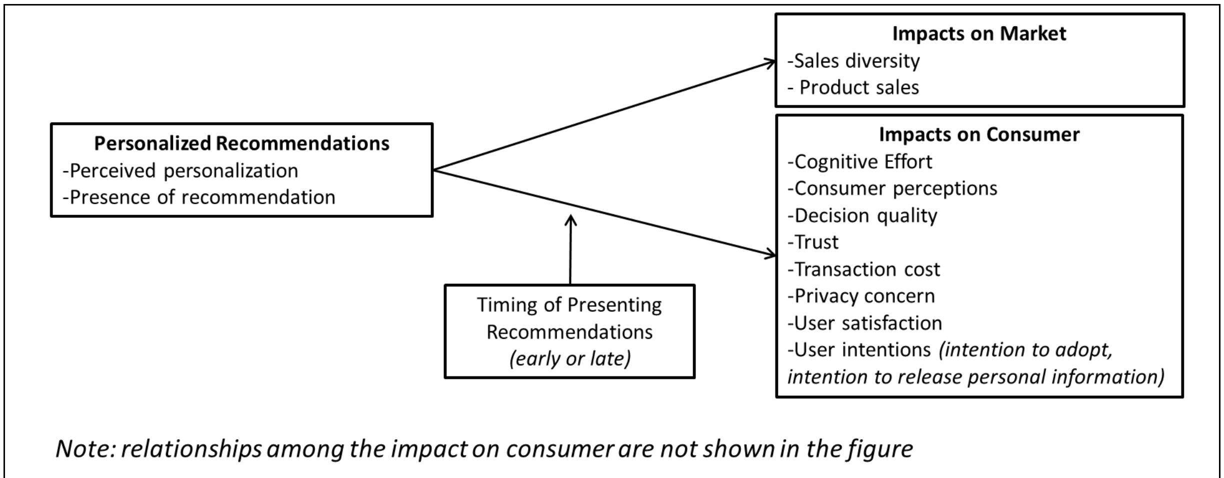

Figure 5. Relationships Investigated in Recommendation System Impacts

Though extant research has enhanced our understanding of the impact of RS, several directions for future research remain. For example, the major focus of research on consumer impacts has been consumers' perceptions. Because the ultimate goal of a recommendation system is to persuade consumers to make more purchases when they visit the e-vendor's website, it would be worthy to also examine how RS affects consumers' purchase decisions. Further, future studies could look beyond the predominant theories used in this area, to include theories and models of decision making, and examine in more depth RS's impacts on a consumer's decision process. Following Ho et al. (2011), a promising avenue for future research would be to examine the phenomenon from a temporal perspective. Using their phases of the consumer decision making process (i.e., attention, cognitive processing, decision, and evaluation) or other similar stage models (e.g., Zeleny (1982): predecision, partial decision, final decision, postdecision), one could examine how RS influences these phases, what type of recommendation presentation features are appropriate for each, and how to time recommendations. Consumers have a different focus and engage in different cognitive activities at each stage (e.g., in the predecision stage, consumers collect product related information to generate alternatives). It would be worthy to investigate how RS and RS features can influence consumers at each decision stage and, thus, affect a consumer's final decision outcome.

At the market level, there is a need for additional studies to resolve inconsistent findings on RS impacts. Such inconsistencies may be due to the presence of moderators such as the type of the focal RS investigated or type of product examined. Another interesting factor at the market level, which Oestreicher-Singer and Sundararajan (2012a) briefly discuss, is product diffusion. Most market-level studies included in this review have examined RS's impacts on sales diversity, which spans across all types of products. A promising avenue for future research would be to focus on a specific type of product and examine how RS influences its diffusion pattern among consumers in the market. The finding will have strong implications for e-vendors, especially when they want to promote the sales of a product in a timely fashion. Further, given Oestreicher-Singer and Sundararajan's (2012b) findings on the effect of RS on complementary products, research on recommendation presentation could examine characteristics of links to these complementary products (e.g., number of links, how complementary products are identified, etc.) and how these influence diffusion patterns and sales. Finally, our review shows that there is scant research on RS impacts at the market level, which is probably due to the difficulty of obtaining such data. As such, it remains fertile ground for future research.

The Missing Impact Level: RS Impacts at the Firm Level

Current RS research focuses exclusively on the impacts of RS on consumers and on the market, which leaves firm-level impacts unexplored. Though e-vendors provide personalized recommendations (presumably because they are of benefit to their business), there is lack of empirical studies on the effect of RS on firm-level outcomes. In addition to increased sales and financial revenues, RS can also influence consumer loyalty (Kasanoff, 2001) that ultimately translates to various tangible (financial) and intangible benefits.

The effect of RS at the firm level can be examined either at the aggregate level or as mediated by consumer-level outcomes. First, the aggregate effect of RS on organizational outcomes can be examined through, for example, a matched pair study of similar online vendors that use or do not use a RS, or by comparing firm sales before and after implementing a RS. By comparing differences in ROI or other firm-level attributes, we can assess RS's impacts on firms. Of course, we can also decompose the RS "black box" and evaluate different RS components impacts on firm-level factors.

The second way to examine RS impacts at the organizational level would be to investigate how individual-level factors mediate the effects on organizational outcomes. The effects of RS on organizational outcomes are likely due to RS's impacts on consumers' purchases, satisfaction, and loyalty. Therefore, multi-level studies that examine how consumer-level outcomes influence organizational outcomes are especially promising. Table 8 summarizes prior studies on RS impacts at both the consumer and market levels.

Table 8. Empirical Studies on the Impact of RS

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
Impacts on consumer				
Awad & Krishnan (2006)	Privacy concern	Willingness to be profiled for personalized service/advertising	Consumer utility maximization theory, privacy calculus	Customers who desire greater information transparency, which is determined by their previous online privacy invasion, concerns, and the importance of privacy policy, are less willing to be profiled for personalization.
Chau & Lai (2003)	Presence of personalization, perceived ease of use	Perceived usefulness; consumer's attitude	Technology acceptance model	Personalization, alliance services, task familiarity, and accessibility were found to have significant influence on perceived usefulness and perceived ease of use.
Chau & Ho (2008)	Presence of personalized recommendations (termed personalization in the paper)	Perceived benefits; consumer-based service brand equity	Consumer brand equity	Personalization was found to indirectly influence consumer-based service brand equity development by mediating the perceived benefits of the brand.
Greer & Murtaza (2003)	Perceived innovation characteristics of personalization (e.g., relative advantage, etc.)	Use intentions	Technology acceptance model, innovation diffusion theory	Relative advantage, compatibility, ease of use, and trialability significantly impacts intention to use personalization; while visibility, image, and result demonstrability were not found to have significant relationship with intention to use personalization.
Häubl & Trifts (2000)	Presence of recommendation agent (RA)	Consideration set size; amount of search for product information; decision quality	Human decision making	RA designed to assist consumers in the initial screening of available alternatives has strong favorable effects on both the quality and the efficiency of purchase decisions.

Table 8. Empirical Studies on the Impact of RS (cont.)

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
Impacts on consumer				
Ho et al. (2011)	Recommendation approach (adaptive vs. static), time of presenting recommendation (early or late)	Consumer satisfaction, quality of recommendations (i.e., accuracy)	Consumer search theory, stopping rule model	The probability that a consumer will choose personalized recommendations is higher if they are presented at an earlier stage; consumer satisfaction will also be higher if the recommendations presented at an earlier stage.
Kumar & Benbasat (2006)	Presence of recommendation agent	Perceived usefulness; social presence.	Technology acceptance model; social presence	The provision of recommendations and consumer reviews increases both the usefulness and social presence of the website.
Komiak & Benbasat (2006)	Perceived personalization,	Cognitive trust, emotional trust, intention to adopt	Theory of reasoned action; trust theory	Perceived personalization significantly increases customers' intention to adopt by increasing cognitive trust and emotional trust.
Liang et al. (2012)	Personalization	Transaction cost, perceived care, perceived usefulness	Transaction cost theory, technology acceptance model	Personalized customer services can generate higher perceived usefulness as compared to non-personalized ones. This relationship is mediated by both transaction costs and perceived care (affect).
Sheng et al. (2008)	Personalization	Intention to adopt, privacy concern	Ubiquitous commerce, privacy calculus	Customers' privacy concerns increase when personalized services are provided. Situational factors greatly influence customers' attitudes, perceptions, and decisions.
Thongpapanl & Ashraf (2011)	Website personalization (e.g., product customization, product recommendation, etc.)	Customer satisfaction; purchase intention; online sales	Perceived risk theory (PRT); Information search theory (IST)	Information that is targeted to an individual customer influences customer satisfaction and purchase intention; customer satisfaction, in turn, serves as a driver to the retailer's online sales performance.
Tam & Ho (2006)	Web personalization, goal specificity	Attention, cognitive processing effort, decision accuracy	User information processing, preference structure construction	Content relevance, self-reference, and goal specificity affect the attention, cognitive processes, and decisions of Web users in various ways. Also, users were found to be receptive to personalized content and found it useful as a decision aid.
Wang & Benbasat (2008)	Reasons for using a recommendation agent	Trust in Recommendation agent	Trust theories, trust reason literature	At the trust forming stage, knowledge-based, interactive, calculative, and dispositional reasoning have positive effects on forming trust in recommendation agents; while calculative and interactive will reduce the trust in recommendation agents.
Xu (2006)	Personalization, entertainment, Informativeness, Irritation, Creditability	Attitude, intention to use	Technology acceptance model	Personalization is one of the most important factors in affecting consumers' attitude toward mobile advertising, particularly for female users.

Table 8. Empirical Studies on the Impact of RS (cont.)

Paper	Independent variables	Dependent variables	Conceptual foundation	Findings
Impacts on market				
Hinz et al. (2011)	Presence of search tools; presence of recommendation system	Sales diversity	The long-tail phenomenon	Search technologies, such as "favorite lists", favor blockbusters and therefore should decrease the share of purchased products; recommendation systems, such as content filters, may increase the long tail and increase the share of purchased products.
Oestreicher-Singer & Sundararajan (2012a)	Presence of recommendation system	Sales diversity	The long-tail phenomenon	Categories whose products are influenced more by the recommendations have significantly flatter demand and revenue distributions, even after controlling for variation in average category demand, category size, and price differentials.
Oestreicher-Singer & Sundararajan (2012b)	Product's degree centrality and complementary/neighbor products' centrality	Product demands/sales	Network theories	The visibility of networks amplifies the shared purchasing of complementary products.
Brynjolfsson et al. (2003)	Increased product availability by enabling technologies (e.g., recommendation systems)	Consumer surplus, product sales	The long-tail phenomenon, consumer welfare estimation	The increase of market efficiency and product availability (e.g., providing personalized recommendations) enhances consumer welfare. This is due to the more-diverse distribution of product sales.
Fleder & Hosanagar (2009)	Existence of recommendations	Sales diversity	Consumer utility maximization	Recommendation systems have concentration bias, which lead to lower sales diversity in the market.

5. Discussion

Figure 6 summarizes the relationships and variables that have been investigated in the extant RS literature in all three stages of the recommendation process. Based on this synthesized view of the extant literature, in this section, we continue our discussion of potential new directions for future research that derive from a more-holistic view across all areas rather than from in each area, which we have already discussed.

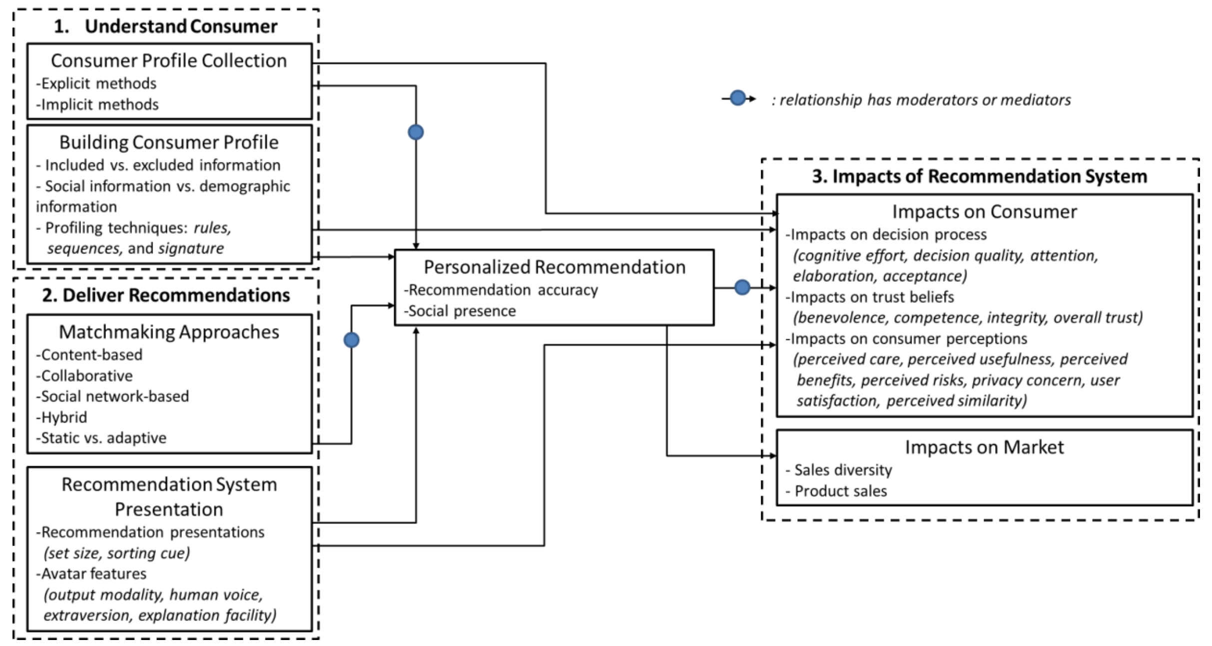

Figure 6. Summary of Prior RS Research

5.1. New Theoretical Lenses

The 41 empirical studies included in our review use 17 different but related theories in examining RS. Table 9 summarizes these theories. Though the diverse set of theories would, at first glance, suggest that a broad range of perspectives on RS have been examined, a closer look suggests that many studies tend to rely on only a few well-established theories, especially in examining RS impacts on consumers. While employing a limited set of theories has the potential to build a cumulative research tradition, a narrow focus also limits the range of research questions investigated. This opens up opportunities for future research on RS that uses additional relevant theoretical lenses to examine questions both in stages and across stages of the recommendation process.

Table 9. Summary of Theories Used In RS Studies

Theory	Number of studies	Studies
Individual-level theories		
Technology acceptance model	7	Chau & Lai (2003), Greer & Murtaza (2003), Kumar & Benbasat (2006), Liang et al. (2012), Qiu & Benbasat (2009), Wang & Benbasat (2005), Xu (2006)
Trust theories	6	Hess et al. (2009), Komiak & Benbasat (2006), Qiu & Benbasat (2009), Wang & Benbasat (2005, 2007, 2008)
Social presence theories	3	Hess et al. (2009), Kumar & Benbasat (2006), Qiu & Benbasat (2009)
Human cognition theories	3	Häubl & Trifts (2000), Lee & Benbasat (2011), Wang & Benbasat (2009)
Social network theories	3	Li & Karahanna (2012), Oestreicher-Singer & Sundararajan (2012b), Park et al. (2012)
Privacy calculus	3	Awad & Krishnan (2006), Sheng et al. (2008), Xu et al. (2011)
Homophily theory	2	Al-Natour et al. (2006), Li & Karahanna (2012)
Information processing theory	2	Liang et al. (2006), Tam & Ho (2006)
Consumer search theory	1	Ho et al. (2011)
Elaborated likelihood model	1	Tam & Ho (2005)
Information search theory	1	Thongpapanl & Ashraf (2011)
Innovation diffusion theory	1	Greer & Murtaza (2003)
Transaction cost theory	1	Liang et al. (2012)
Theory of reasoned action	1	Komiak & Benbasat (2006)
Market-level theories		
The long-tail phenomenon	3	Brynjolfsson et al. (2003), Hinz et al. (2011), Oestreicher-Singer & Sundararajan (2012a)
Consumer utility maximization	1	Awad & Krishnan(2006), Fleder & Hosanagar (2009)
Consumer brand equity	1	Chau & Ho (2008)

As Table 9 summarizes, trust theories and TAM are used more frequently than other theories (used in 13 out of the 27 (48%) individual-level studies). Trust theory helps us understand how consumers form trust beliefs toward personalized recommendations (Komiak & Benbasat, 2006; Qiu & Benbasat, 2009) and how trust beliefs influence consumer opinions of RS (Wang & Benbasat, 2005). TAM explains RS impact on consumer perceptions and subsequent behaviors (Greer & Murtaza, 2003; Kumar & Benbasat, 2006). Both theories provide excellent starting points to study RS. However, additional theories will add richness and can yield complementary insights.

For example, since consumers play a key role in the personalization process, consumer cognition and behavior demand closer attention in RS studies. Cognitive theories in psychology and decision making theories and theories of persuasion provide a range of theoretical lenses to study RS. We have already discussed some of these in our review as fruitful areas for future research. The online environment is information rich and thus individuals are inundated with information. Information processing theories assert that an individual's information processing capability is limited. According to Simon (1971), "a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it" (p. 40-41). Therefore, individual consumers perform trade-offs between cognitive effort and decision accuracy (Bettman, Johnson, & Payne, 1990; Johnson & Payne, 1985) when browsing and shopping for products and services online. E-vendors can develop various tools to attract consumers' attention or channel their information processing. RS studies that approach the phenomenon from this perspective have the potential to greatly inform RS presentation and provide actionable guidelines on how to organize and present recommendations to enhance consumer decision outcomes.

Consumer preference construction is another promising theoretical perspective in understanding consumer preference elicitation. Consumer preferences are not static but dynamic (Slovic, 1995) and they can be influenced by personalized recommendations (Häubl & Murray, 2003). As such, a consumer typically does not have well-identified preferences that are stable and invariant to the context (Bettman et al., 1998). The preference construction process is an interaction between the consumer's information processing characteristics, task properties, and the information space (Payne et al., 1999). As a result, consumer preferences have both a stable component emanating from inherent preferences and a dynamic component that emerges as consumers encounter and process more information. In the context of RS, this implies that consumer preference elicitation needs to understand both inherent preferences that are temporally stable but also dynamically updated preferences. Thus, new profile-building and matchmaking approaches should take into account the constructive nature of consumer preferences to enhance recommendation accuracy. Further, studies that examine the impact of RS on the consumer decision making process could examine how provision of recommendations influences the consumer preference construction process and ultimate purchase decision.

5.2. Relationships among RS Components

One benefit of an integrated framework (Figure 6) is that we can easily identify research gaps in the current literature. As we can see in Figure 6, most prior studies focus on direct effects between the various RS components in the framework. Few have investigated interactions among them. Nevertheless, investigating interactions can contribute to both practice and theory.

For example, the interaction among consumer decision making strategy, RS presentation, and matchmaking approaches could be a promising research direction to follow. Al-Natour et al. (2006) found that consumers were more likely to trust RS and accept the recommended products when they perceived a high similarity between the RS's guidance and their decision strategy. This shows that the alignment between consumer decision strategy and RS presentation does lead to desired outcome. Then, how about the alignment between decision strategy and matchmaking approach (e.g., content-based, collaborative, or social network-based)? This requires both theoretical and empirical studies to examine and may be a fruitful direction for research. Furthermore, given that consumers have different decision strategies when making choices (Johnson & Payne, 1985), how an RS estimates an individual consumer's decision strategy so that it can align it with an appropriate RS generation or presentation approach is another interesting question that is worth investigating in the future.

Further, the recommendation process model that Adomavicius and Tuzhlin (2005) suggest includes feedback from recommendation impacts back to understanding consumers and recommendation delivery. Proper feedback loops can "achieve the virtuous cycle of personalization, and avoid the trap of depersonalization" (Adomavicius & Tuzhlin, 2005, p. 89). Nonetheless, the studies we reviewed consider recommendation impacts, either on consumers or on the market, as the ending point of the whole recommendation process. Understanding the data that need to be collected and the mechanisms via which adjustments are made in order to deliver more-accurate recommendations in the future would be a fruitful direction to pursue.

Finally, social network navigability, whether through social networks of consumers or social networks of products (e.g., Oestreicher-Singer & Sundararajan, 2012a, 2012b), provides a new lens via which to examine how recommendations can be generated in a more dynamic manner and one that allows consumers more control over the process of matchmaking. Further, examining the interplay between social networks of consumers and social networks of products with respect to recommendation systems can provide useful insights for constructing consumer profiles and matchmaking.

The above discussion is not meant to be an exhaustive list of potential future directions for RS studies. The purpose of the discussion is to illustrate some possibilities for future research that use different theoretical lenses than those found in extant RS studies and the insights that such perspectives can generate. There are clearly many other theories that can guide RS research and many potential research gaps to fill. These form promising future directions. Furthermore, the “big data” online environment and the explosion of social media and of social networking platforms present new opportunities for research on RS by providing a wealth of different types of data to mine (e.g., unstructured data, social network data) to derive personalized recommendations. They also highlight the increasing importance of providing “accurate” personalized recommendations to help individuals deal with the “abundance of information and poverty of attention” that Simon so aptly describes (Simon, 1971).

6. Limitations

The studies we included in our review are empirical studies from a set of IS journals and conference proceedings. Our discussions also draw on selected studies from other fields to help us explain relations among factors and build the overall framework. Nonetheless, the scope of this study is limited to the IS field. It is possible that review of RS studies in other fields can reveal additional factors not examined in IS studies. Therefore, it is worthwhile for future studies to conduct similar reviews on RS research outside the IS field. In addition, the review focused on empirical studies and excluded studies on conceptual and algorithm design. Such studies are important because they provide valuable guidance for future RS research and RS design.

7. Conclusions

In this paper, we conduct a literature review of empirical studies in recommendation systems. We first review various definitions of RS across studies and focus our attention on RS that provide personalized offerings to individual consumers. We identify three major stages of the recommendation process: understanding consumers, delivering recommendations, and impacts of RS. We conduct a review of the extant RS literature in each stage and discuss the emergent constructs and relationships. Through the discussion, we reveal research gaps in current RS research, we propose new research directions and theoretical perspectives for each stage, and make suggestions for future research in RS as a whole.

More generally, we find the literature on RS to be fragmented and lacking an overarching framework to systematically guide research and to integrate findings. We believe that the framework we use in this study can provide one potential overarching framework (Figure 6) for research in this area. It provides a comprehensive view of the personalization process, includes both the relevant technological (system side) and behavioral (consumer side) aspects of RS, and allows for one to integrate research both in a stage and across stages. As such, it provides a useful integrating mechanism to summarize the extant state of understanding, to surface gaps, and to generate opportunities for future research.

Our review concludes that research in RS is still at a nascent stage and that more studies are required to enhance our understanding of RS, its components and how they interact, and its impacts. The shifting landscape of social media, social network data, and the abundance of other digital consumer data (both structured and unstructured) opens up new challenges and opportunities in this area for both theory and practice.

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Appendix: Empirical Studies included This Review

In this review, we discussed 41 empirical studies. Table A1 is the list of journals and conferences, and all 41 papers with their author names and publication year.

Table A1. Papers Included in this Review

Journal/conference name	Papers selected
Communications of the ACM	Adomavicius & Tuzhilin (2005)
Decision Support Systems	Xu et al. (2011)
European Conference on Information Systems	Gottschlich et al. (2013)
Hawaii International Conference on System Science	Li & Karahanna (2012), Shih & Liu (2005)
Information & Management	Kumar et al. (2004)
Information Systems Research	Ho et al. (2011), Kumar & Benbasat (2006), Lee et al. (2011), Tam & Ho (2005)
International Journal of Human-Computer Studies	Lavie et al. (2010), Ochi et al. (2010)
Journal of Computer Information Systems	Greer & Murtaza (2003), Thongpapanl & Ashraf (2011), Xu (2006)
Journal of Management Information Systems	Hinz et al. (2011), Liang et al. (2006), Qiu & Benbasat (2009), Wang & Benbasat (2007, 2008)
Journal of Electronic Commerce Research	Liang et al. (2012)
Journal of the Association for Information Systems	Al-Natour et al. (2006), Arazy et al. (2010), Hess et al. (2009), Sheng et al. (2008), Wang & Benbasat (2005)
Management Science	Brynjolfsson & Simester (2011), Brynjolfsson et al. (2003), Fleder & Hosanagar (2009), Oestreicher-Singer & Sundararajan (2012)
MIS Quarterly	Awad & Krishnan (2006), Komiak & Benbasat (2006), Oestreicher-Singer & Sundararajan (2012), Park et al. (2012), Tam & Ho (2006), Sahoo et al. (2012), Wang & Benbasat (2009)
Others (i.e., non-IS journals)	Häubl & Trifts (2000), Häubl et al. (2003), Chau & Lai (2003), Chau & Ho (2008)[5]
Total	**41 studies**

[5] Selected papers from other journals were used to support certain relationships in our discussion.

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