RECOMMENDATION AGENTS: HOW TO BUILD AN EFFECTIVE SYSTEM

by

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ABSTRACT

Recommendation Agents are an information filtering system that helps identify consumers preferences based on previous purchasing behaviors, or ratings, of a product. Many researchers have looked at different components of the RA systems, but this paper will provide a complete framework of how RA systems work and where they are going in the future. RAs help drive consumer sales through various different algorithms and techniques such as content-based filtering, collaborative-based filtering and co-clustering. RA could take many paths in the future such as looking at each individual click on a computer, personality types, or even moving forward to see how RAs could be used on tablets in stores while consumers are shopping.

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Recommendation Agents: How to Build an Effective System

Recommendation Agents (RAs) are an information filtering system that helps identify consumers preferences based on previous purchasing behaviors, or ratings, of a product. For example, whenever a consumer is online shopping and there are related, or recommended, products that appear at the bottom of the screen, this is the result of RAs. RAs drive purchasing power and take a deeper look at how consumers make buying decisions.

Several articles examined the effectiveness of RAs and how consumers perceive their quality and trust in the system. A cornerstone article states that RAs improve customer decision making and reduce efforts for the consumer (Xiao & Benbasat 2007). When a consumer sees an RA as trustworthy, this will positively influence the likelihood that the consumer will adopt the agent or purchase the product (Wang & Benbasat 2005). One study has found that effective RAs explain how they have selected the recommendation for the user, increasing their trust in the purchase (Komiak & Benbasat 2004). However, research has mostly focused on the broader topics of what makes an RA effective in different components, and there is little academic research on a complete framework of how an RA system works from start to finish.

In this paper, I will identify what components of an RA system are most effective. This will help highlight how consumers' perception of online shopping can be increased through building an optimal RA system. Additionally, I will state what direction RAs are going in and propose a new option for how RAs can be used to increase consumer sales and satisfaction in stores.

RAs are most effective when they are constructed with several combining attributes at one time. Previous research indicates that utilizing a balance of transparency to increase customer satisfaction without presenting too many options, content-based filtering, collaborative-based filtering, and determining an appropriate price point consideration while purchasing will all increase the effectiveness of the RA system. Additionally, two proposed items to go into building an effective RA system would include taking a closer look at the time spent on each page while shopping, and tracking which consumers actually have used and made purchases from recommendations to track which products could be most effective for further marketing and promotion

Overview of Recommendation Agents

Recommendation Agents (RAs) are defined as "software agents that elicit the interests or preferences of individual users for products, either explicitly or implicitly, and make recommendations accordingly" (Xiao & Benbasat, 2007, 137). Due to the prevalence of online shopping and consumer response rates to various forms of marketing, RAs are becoming a growing asset to many companies. If marketers can determine how to most effectively assign and allocate information from RAs, marketers can increase product awareness and profits. RAs have the power to not only increase sales, but also increase customer loyalty by recommending products that the consumers can find additional value in based on their individual preferences (Berman 2002).

RAs can be utilized in several different forms. Although RAs can be used for in-store shopping by printing out targeted coupons at the checkout counter, the focus of this paper will be e-commerce RAs. An example of an e-commerce RA includes when companies, such as Amazon, recommend products at the bottom of the screen after you have put an item in your shopping chart or make a purchase. These products are recommended to consumers based on previous purchase patterns using technology or online mediums to make the recommendations to consumers.

There are several characteristics of RAs. RAs are used by companies to help ease the decision-making process for the consumer while reducing the amount of effort required (Xiao & Benbasat 2007). RAs help save consumers the time and effort that would be required to thoroughly evaluate all alternative options available. Decision time and extent of the products searched are used to evaluate products that have been considered by the consumer to make further recommendations.

RAs can be broken into two main filtering methods that are the inputs to RA systems, known as content-based filtering and collaborative-based filtering. Content-filtering RAs use consumers' desired product attributes to create recommendations. Collaborative-filtering uses the opinions of other consumers who are shopping for similar products or exhibit similar shopping pattern behaviors (Ansari et al. 2000). The personalized scoring model uses a point-based system algorithm to determine matching behavior (Zhu, Song & Zhang et al. 2008). All of these filtering RA types will be discussed in further detail later in the paper along with several other filtering algorithms.

RAs can also be broken into several models and methods. Co-clustering is similar in that it groups like-minded users based on different categories they fit into. One point that is important to keep in mind with co-clustering is the trust and integrity of the system. Individuals do not want to place too much importance on the system if faulty matches are being made (Shinde & Bag 2015). Lastly there is a distinction between “smart” and “knowledgeable” RAs and how they can be effectively used to target to the proper audience.

RAs can be classified by several types of decision strategies. Compensatory RAs consider trade-offs between attributes, such as price, functionality features, and reviews, whereas non-compensatory RAs do not consider trade-offs. Compensatory RAs improve decision making, but may increase decision effort required. Additionally, there is a needs-based RA category that emphasizes the recommendation by asking what the customer needs, acting as an expert within the system to find products best fitting the needs. Feature-based RAs are decision assisted and look at particular features that a consumer has selected (Xiao & Benbasat 2007). For example, if a consumer is interested in a product that has a long battery life, the RA will assist the consumer in identifying products that possess the battery life expectations that the consumer has selected.

Each category of RAs provides a different set of costs and benefits to the consumer, which in turn creates different outputs. The type of industry that the product is being sold in should influence what type of RA system a company chooses to employ. Studies show that a hybrid of RAs leads to improved decision quality, but higher decision effort. An overload of recommendations leads to greater decision effort and lower decision quality. Building an effective recommendations system produces a sorted list of recommendations that rely on heuristic decision strategies to determine the best alternative options (Xiao & Benbasat 2007). The outputs decide whether or not the consumer will be satisfied with the RA they were provided with.

Different algorithms can be utilized to best assist a consumer in selecting a product based on a RA. The quality of a consumer's decision is dependent on several factors. If too many options are presented, consumers will quickly feel fatigued and unsatisfied with sifting through the numerous options. Most people like to work efficiently to save time and effort, which is where the RA systems help ease the process. Consumers will make better choices, and therefore have a happier and more satisfied outcome, when the number of options presented are limited and it is clear to determine how the recommendation was provided to the consumer (Xiao & Benbasat 2007).

Expanding out to deeper meaning from the use of these systems, RAs have important implications on marketing. The degree of trade-off transparency in displaying product qualities and price influence consumers' willingness to spend time researching and purchasing products. The degree of trust present within the RA system is highly correlated with the amount of time required for consumers to review the recommendations and decide if they will purchase (Xu & Benbasat 2014).

Perceived Usefulness of Recommendation Agents

Consumer perceptions of an RA greatly influence how useful the consumers view the recommendations. If a consumer believes that a product recommendation is useful, this positively impacts the consumer's intentions to accept the RA system as a whole. Similarly, if a consumer perceives that an online RA is easy to use, the consumer will believe that the RA is more useful in making recommendations and trust the recommendations more (Wang & Benbasat 2005).

Swaminathan (2003) had an opposing view of RAs that have been discussed thus far in the paper. Research done by Haubl and Trifts (2000), along with others previously mentioned, have found that RAs do have an impact on the decision quality. However, Swaminathan (2003) found that RAs did not have an impact on increasing decision quality for consumers shopping online.

When RA systems offer a fewer number of recommendations, the consumer could more easily identify the best option because there were not as many miscellaneous items to sort through (Swaminathan 2003). This helped reduce consumer decision making time and effort and increased consumer satisfaction. This view does hold true with several other researchers who state that there needs to be a balance in the number of RA options presented to the consumer (Xiao & Benbasat 2007).

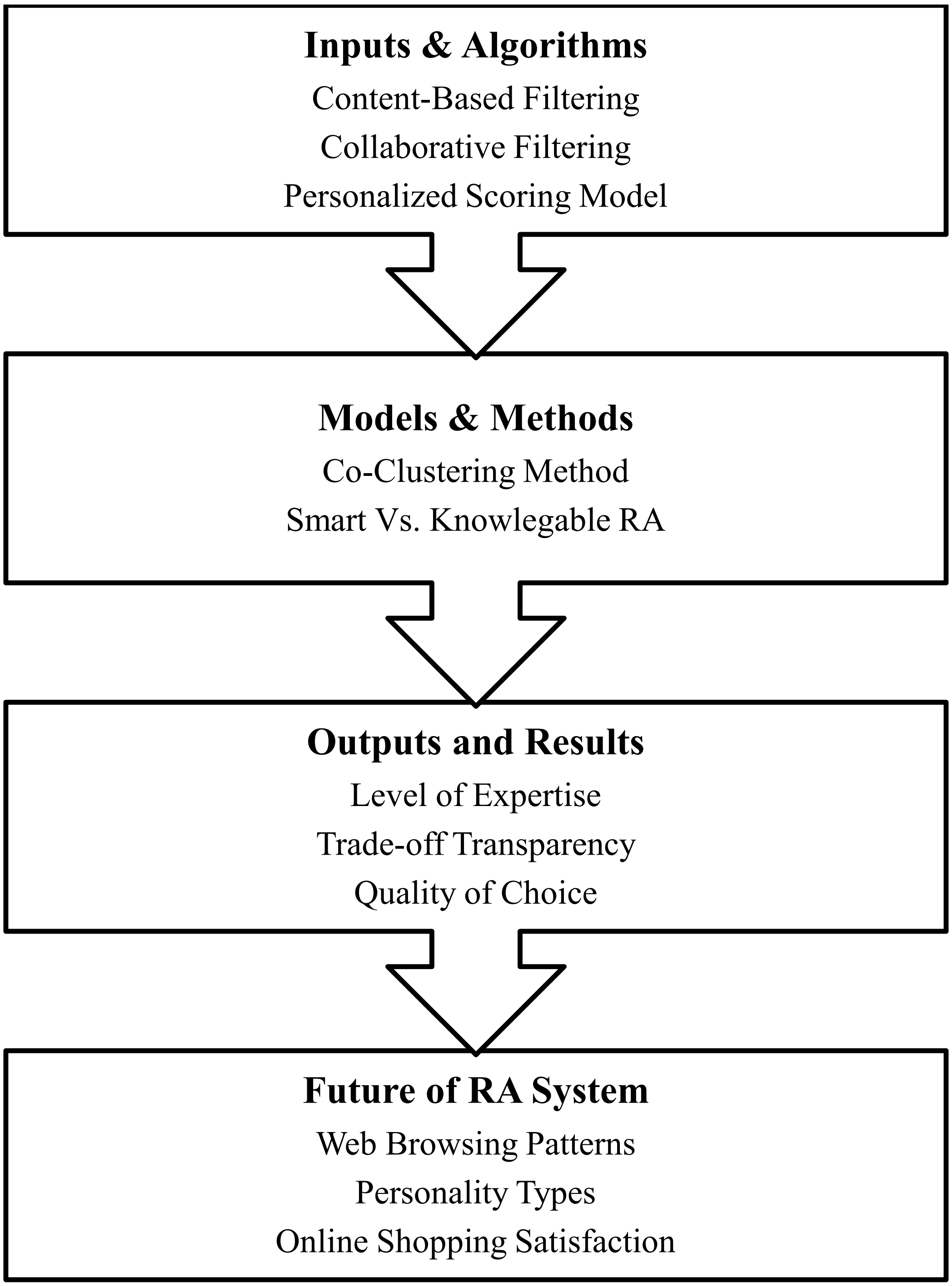
RAs can be overwhelming if too many options are presented. The greater the number of attributes of the product, the greater the number of dimensions there are to evaluate the product. This makes it difficult to find the correct option for the consumer. For complex products, RAs would be most useful from "first narrowing the set of attributes based on a non-compensatory elimination-by-aspect approach and then presenting consumers with the shortlist of attributes" (Swaminathan, 2003, 101). This reduces the amount of stress on the consumer and increases perceived decision quality.

One interesting case study focused on the book industry and described the author's personal experiences with different RA systems available online. Amazon's RA system is described as using consumer reviews as a part of their algorithm, which was not preferred by Charman-Anderson (2015) because it would often recommend books that were not to his particular liking.

On a platform called GoodReads, the RA system works as you enter in books you have read and rate them, and then a list is generated based on your specific preferences. It is also notable to add that there is cover art and graphics which made a significant difference in consumers selecting this system as more effective. It was important to the author that not too many options were presented at one time. He said that this became overwhelming and it was just as difficult to select a book from a long list as it would have been without the RA system providing options (Charman-Anderson 2015).

The above case study supports implications that having too many options will decrease consumer satisfaction in RA systems (Xu & Benbasat 2014). Construction of an RA system requires consideration of the number of options presented to consumers.

Overview Model of Recommendation Agents



Algorithms used in Recommendation Agents: Inputs

Content-Based Filtering

Content-based filtering picks information based on other items with a high co-relationship (Shinde & Bag 2015). Content-based filtering systems use several different techniques to see if information matches up. Key word filtering searches for key words you want to find and blocks words you do not want to pull up in a search. For example, if you do an advanced search on Google, you can use key word filtering by populating the fields with words you require and exclude from the search. If you are searching for Benjamin Franklin Plumbing you can search for Benjamin and Franklin, but exclude plumbing. This will help narrow the search results presented to a list of items that are actually being looked for through the search. Phrase filtering is an extension of key word searches and works similarly, but allows you to require and exclude phrases as a whole from the search skin (Chowhan, Deshmukh & Kolhe 2015).

Another type of content-based filtering system is profile filtering, which filters online websites based on different factors such as the picture-to-text ratio and links to other websites. Profile filtering is useful when a consumer is trying to do research in a particular area and may require more pictures or links than other websites. An image analysis filtering system specifically filters through images and blocks out inappropriate pictures that may show inappropriate items, such as too much skin or profanity (Chowhan, Deshmukh & Kolhe 2015).

There are several different types of content-based filtering that can be manipulated and explored to increase website exposure and produce recommendations for consumers. Content-based filtering can “directly select information based on a user own profile contents without the opinions of other users, while collaborative filtering can recommend information according to other opinions" (Chowhan, Deshmukh & Kolhe, 361, 2015).

Collaborative Filtering

Collaborative filtering matches purchasing patterns and browsing behaviors to link similar users providing common recommendations. Collaborative filtering often delivers more accurate information that is better suited to consumers than alternative methods (Titiriga 2011). For example, collaborative filtering looks at the big picture to determine what similar users have purchased and make similar product recommendations based on similar consumers' behaviors. If an individual was shopping online for a blanket that was a particular color and size that another consumer had searched for and purchased, an RA system using collaborative filtering would recommend the blanket purchased by the consumer to the individual shopping online.

There are three main categories of collaborative filtering: Item-based collaborative filtering, memory-based collaborative filtering, and model-based collaborative filtering (Zhu, Song & Zhang et al. 2008).

Item Based Filtering

Item-based collaborative filtering evaluates the relationships between the current and future items being looked at. A weight is assigned to all of the reviewed projects to help create a recommendation. There are two main issues when looking at item-based collaborative filtering which are the scalability of the algorithm and the quality of the RA system (Zhu, Song & Zhang et al. 2008).

Memory Based Filtering

Memory based filtering is similar to collaborative filtering, and can be further enhanced by incorporating contextual information to increase the quality of recommendations (Tseng &

Lee 2015). Similarity is measured by user preferences and different contexts. Recommendations are produced based on the similarity of other users who have a similar taste to the consumer based on historical ratings of products. Additionally, the nearest neighbor method is adopted, meaning that the system predicts products with a grouping of ratings of users that are closest by (Tseng & Lee 2015).

Model-Based Filtering

Model-based filtering looks for a latent factor as the basis for user product-rating. The model predicts that if the latent factors can be identified for a user, their rating could be predicted based on these factors. Different algorithms have been derived to determine the differences between predicted and observed ratings (Tseng & Lee 2015).

Personalized Scoring Model

In the personalized scoring model, “a recommended project exists as an agent and every recommended project is a recommended subject, that is recommended agent” (Zhu, Song & Zhang et al., 178, 2008). The system assesses each recommendation’s relationship with another and uses the behavior and user history when evaluating recommendations. Each item is then scored based on its relationships to other users and the system to calculate similarity within the algorithm.

The diagram below depicts the relationships between different recommendation agents within the system. The top recommendation set is generated based on user preferences. This score is used to create a recommendation for the user.

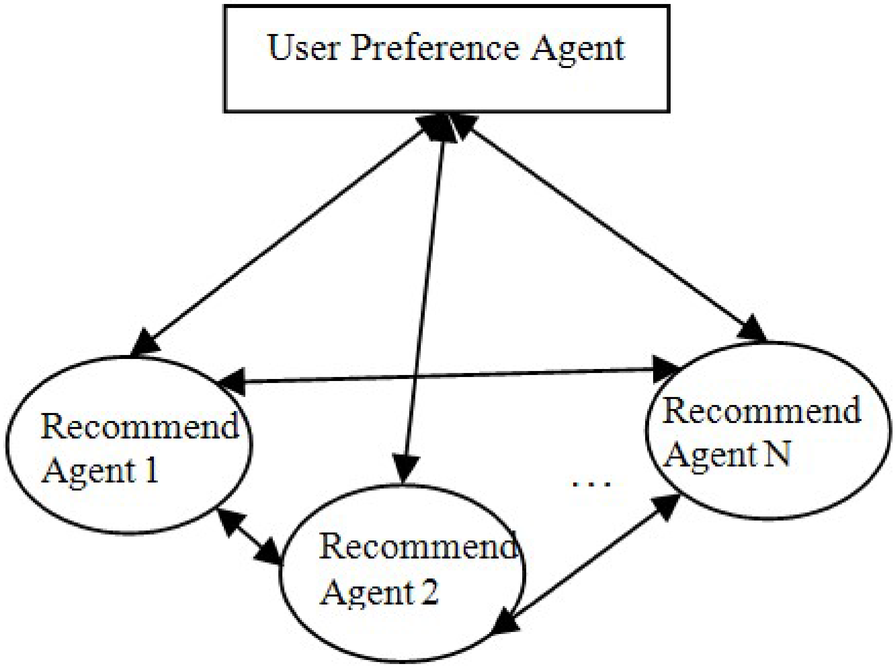


Figure 1: Scoring Model structure based on multi-agent (Zhu, Song & Zhang et al. 2008).

Models and Methods of Recommendation Agents

Co-Clustering Method

User-based collaborative filtering focuses on making recommendations based on like-minded users while collaborative filtering makes recommendations of consumer items that are highly related (Shinde & Bag 2015). Co-clustering involves dividing all products into categories, forming user groups who fit with each type of category, and then fitting into a user matrix category to determine products that should be recommended for the different levels of users within each group.

For example, if consumers are looking at candy, we could divide the candy into categories such as chocolate, gummy, etc. Then the consumers would be divided into groups based on their preferences for chocolate or gummy candies. Users' individual preferences within each category will be calculated within the RA system to determine similar users and make recommendations based on those preferences and purchasing behaviors.

Use of a co-clustering method should not to rely too much on recommendation predictions from the system. If these recommendations are seen as invalid by consumers, there will be a loss of trust within the system. As previously mentioned, it is very important for consumers to maintain trust within an RA system or they may abandon the RA system all together (Shinde & Bag 2015).

Consumers who lose trust can abandon the entire RA system. Reduced trust leads to an increased amount of time and effort required by the user to select a product. If this is the case, the consumers may become fatigued looking for a product and abandon their search all together. If this happens too frequently, it could lead to a significant decrease in sales, causing problems for retail business. Use of the co-clustering method requires consideration to ensuring that trust is maintained within the RA system to evaluate products (Shinde & Bag 2015).

Smart Versus Knowledgeable Recommendation Agents

According to Punj and Moore, RAs can be defined as “smart” or “knowledgeable.” RAs that are “smart” sort through and integrate information and offer feedback to the consumer. “Smart” RAs help the consumer understand more about alternative options, facilitating learning for the consumer. “Knowledgeable” RAs simply know of alternative options in the market place but do not provide any sort of feedback (Punj & Moore 2007).

“Smart” RAs lead consumers to do less research and consider a greater number of alternatives. Consumers are more easily influenced by the recommendations presented when shopping online and will look at a wider array of options available. Consumers are more likely to use the feedback from a “smart” RA system to save effort and still find a good product fit for what they are searching for. Consumers who utilize “smart” RAs are often more trusting overall of the entire recommendation system.

The above factors all lead to higher customer satisfaction because the consumers feel as if they successfully found a good product without spending as much time researching each individual option, but rather trusting the online algorithm systems of the RA. “Smart” recommendations help facilitate learning on the part of the consumer to identify what attributes they need most (Punj & Moore 2007).

“Knowledgeable” RA systems are not as intuitive as “smart” recommendations. “Knowledgeable” recommendations may suggest that a new criteria for selection should be modified, but it will not give a further recommendation beyond that. In simpler terms, the “knowledgeable” RA will merely provide the alternative options provided by the retailer as opposed to targeted recommendations based on the particular product being viewed. The lack of feedback leads to a much higher degree of options that are searched when selecting a product (Punj & Moore 2007).

When constructing a RA system, managers should consider what the intended and unintended consequences of placing these recommendations online via a computerized system. Punj and Moore (2007) also found that if consumers are willing to invest more time into their search, they will use less effort while still making a more accurate decision when using a “smart” RA. It is important to keep both “smart” and “knowledgeable” RA systems flexible to adapt to the quickly changing market place. Although consumers seem to lean more towards using “smart” RA systems, it is still important to keep consumers informed of the decisions they are making.

Outputs and Results of Recommendation Agents

Level of Product Expertise

Consumers who have a high level of product expertise do not need to rely on the recommendations of an RA as heavily as the average consumer (Kramer 2007). A product expert is someone who is very knowledgeable about a particular product based on their industry knowledge or experiences. For example, a consumer could be a product expert if he or she has spent a lot of time researching different tablets on the market. They will know the different qualities about different brands and models such as the dimensions, camera quality, battery life, storage space and customer reviews of the products. However, product experts may be able to more easily navigate and utilize RAs if they are more familiar with how the systems work in general. Low expertise groups may find it difficult to effectively use recommendations if they are not familiar with the RA system (Anh & Park 2012).

Xiao and Benbasat (2007) proposed that the greater the consumer's product expertise, the less they will rely on the RA as a source of feedback. Product experts will fall back on their own knowledge and may lose trust in RA systems if they are recommended products different from their own personal beliefs. For example, if a consumer is a product expert on cell phones and determines that phone A has better picture quality than phone B, but phone B is continually recommended, the consumer may lose trust in the RA system because he or she does not support the products recommended.

When RA systems recommend products of a lower price, consumers begin to make trade-offs of what they wanted in the product. If they are not product experts, consumers may overestimate their need of the product, leading to purchasing a high power product at a greater price.

For example, if a consumer is searching for a new fitness watch with the purpose of tracking the time while he or she is running, they may not need a Nike fitness watch that tracks a variety of additional variables. The consumer could find a reasonably priced sports watch for a fraction of the price and still satisfy their need. When consumers make this trade-off and purchase a higher power product than they truly need, trust is lost in RA systems (Wang & Benbasat 2007).

Trade-Off Transparency

Trade-off transparency refers to how easy it is to differentiate products based on price, attributes, or functionality based on the RAs. As trade-off transparency rises, the consumer has to evaluate a greater variety of products. The greater the burden placed on the consumer, the more difficult it will be to make a satisfying decision. The goal of an effective RA is to find a balance of transparency of the product as well as perceived enjoyment in the shopping experience (Xu & Benbasat 2014).

A user who is aware of why an RA system works as it does can gain a deeper understanding of the product (Xu & Benbasat 2014). When an RA is seen as easy to use, there is a favorable impact on the perceived helpfulness of the RA and effectiveness of the purchase choice. The perception of the ease of use is important in evaluating the trade-off transparency (Anh & Park 2012). Xu and Benbasat (2014) found that consumers who understand the value of trade-offs of different products can still maintain a positive degree of satisfaction. For example, if a consumer is shopping for vacuum cleaners and a recommendation is produced with a new vacuum that also has a removable hand-held component at a higher price, the consumer will need to understand the function of this additional component to effectively evaluate the trade-off.

For RAs to effectively persuade consumers to purchase recommended products, the RA system needs to explain how the different recommendations were produced. Recommended products may be labeled as 'Recommended for you based on your purchase of product X,' which instills confidence in the consumer when they are seeing a particular product. When RAs are highly persuasive, they generally gain greater acceptance by consumers (Sherrie & Benbasat 2004).

Wang and Benbasat (2007) highlight that explanations of how a RA works enhance the consumer's first trusting beliefs about the RA. When the RA is explained based on how it produces the recommendations, consumers feel less as if the products are generated by a computer algorithm and more as if they are receiving a recommendation from a personal shopping assistant while they are browsing. This depicts how important RA systems are in increasing and driving sales for online mediums, especially when attracting new customers and promoting their products.

Going one step further to explain not only what a RA system is, but to describe how it works, increases both competence and benevolence beliefs. When RAs are transparent about their reasoning, consumers may perceive that the RA will produce predictable results. Predictable results will align with their evaluations, therefore reinforcing their results (Wang and Benbasat 2007). The clearer an RA system is about the variety of products available for consumers to select from and purchase, the more likely the consumer is to trust the recommendation as valid.

Quality of Choices

Consumers who are dealing with trade-off transparencies should consider the quality of choices. With the growing pace of technology, consumers are overloaded with choices. This overload can easily fatigue consumers when selecting the best product due to the large amount of information processing.

When the amount of effort required is greater than the limits of processing, decision quality will suffer (Henry 1980). This means that if the consumer has to spend more time understanding what the product is compared to their capacity to understand the product in the limited amount of time they are willing to spend shopping, then the quality of the choices they are making will suffer.

Choice quality suffers as overload increases. If you place too much marketing and advertising or a large variety of product features online, then the consumer will not be able to make the most appropriate decision for what they are looking. Using an RA system for more complex product will increase the quality of a decision by focusing on the alternatives that are most fitting to the consumers' needs and preferences (Xiao & Benbasat 2007).

RAs support and improve decision quality because it reduces the degree of the overload of information presented within the system. For example, computers often rely on RA systems because there are many qualities that consumers will consider such as processor size, battery life, weight, speed, etc. Consumers will make better choices when there are fewer recommendations presented with a more targeted message as to why this product, or alternative computer, is best suited for the consumer.

Simon (1955) highlighted how humans behave like satisfiers as opposed to optimizers. This means that humans just want to make sure that they are satisfying their needs, not necessarily always looking at whether they have made the optimal choice. Perceived overload can cause dissonance and distress for consumers even if there is not as high of a degree of options as the consumer perceives. RAs help reduce and organize the number of options initially presented to consumers.

The Future of Recommendation Agent Systems

Research has shown that many RAs rely on content-based filtering and collaborative filtering to produce recommendations for consumers (Titiriga 2011). However, some are looking to the future to see what new ways RAs can be utilized to help increase and drive consumer sales. Ganapathy (2010) stated that new RAs will start to look beyond past behavior of purchasing or browsing products, to narrow in on implicit information about consumer's web browsing habits. Lastly, Zhu et al. (2015) make claims about how online shoppers prefer the lower levels of societal stress and the impacts of impulse decision buying.

Different web browsing patterns could include the specific buttons clicked on while navigating a page. These clicks may be monitored to take a deeper look into building a RA system. The amount of time spent on a page, and each of the different items clicked on each page, will all contribute to a more sophisticated and targeted RA system to generate recommendations (Ganapathy 2010).

Others have even researched the possibility of using personality types in an RA to help determine appropriate recommendations for consumers (Quan 2013). The strategy was based upon the concept that users could be classified according to a character so that their preferences would match their personality and their evaluations could be grouped among users with similar characteristics. The concept was built upon being an extended form of collaborative filtering. By the use of personality types, recommendations could be further targeted to fit the consumer's needs.

The consumer's personality types could be obtained explicitly or implicitly from a personality exam or from online patterns and behaviors respectively. An individual's character remains relatively consistent, which would reduce the amount of times the RA system would need to be updated. However, it is noted that this type of RA system would take time because there is not currently an easy way to obtain different user's personality types for new users. There is still room for more research in this area, and this could be the future of RA systems (Quan 2013).

One area that has been researched recently includes a study performed by Zhu et al. (2015) that looked at the relationships between RAs and impulse purchasing by applying the SOR (Stimulus-Organism-Response) model. They proposed that the stimuli of RAs affected consumer attitudes and behaviors. Below is a diagram of their hypothesized study that depicts the input and outcome variables.

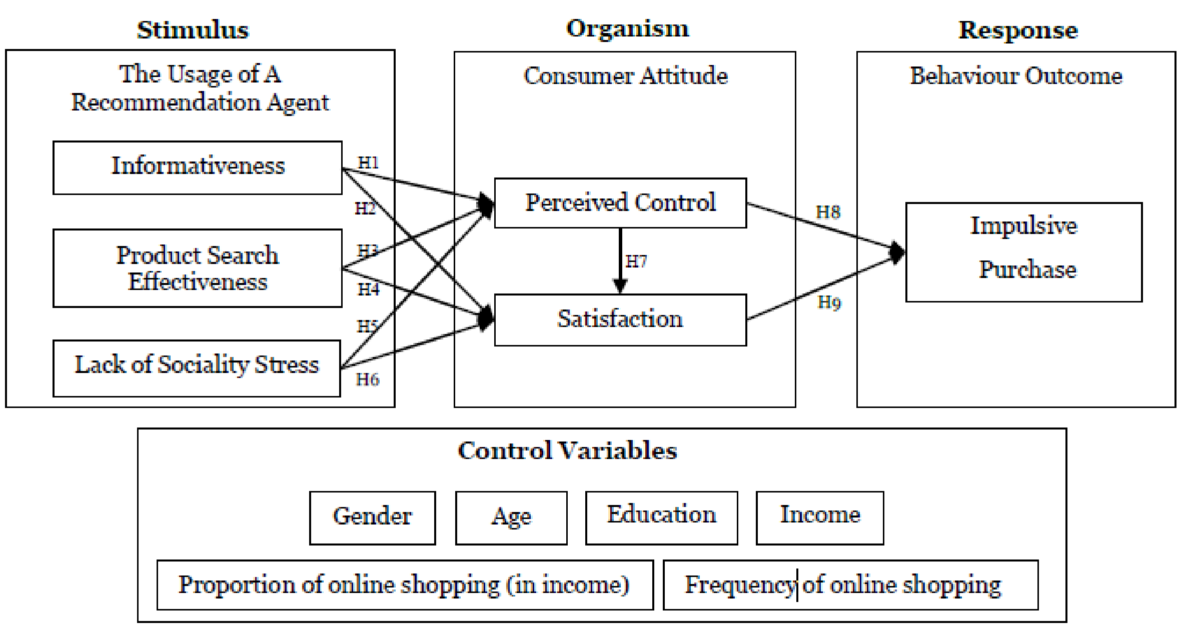


Figure 2: Proposed Research Model for RA Satisfaction (Zhu et al. 2015)

The study found that consumers preferred online shopping because they were able to escape nagging sales associates and shop on their own time. When the RA system makes a personalized recommendation, consumers established "emotional and social bonds with RAs" and were more likely to make a purchase (Zhu et al., 2015, 11). The researchers identified that online shoppers found most satisfaction from the RA when they did not have a lot of time and were early, heavy users of the internet. RA systems can use this information to establish a more effective system for their online shoppers in the future.

Online shopping has been growing at a rapid rate (DeNale & Weidenhamer 2016). The above information could imply significant marketing techniques that can be used to increase impulse purchases and overall sales. Industry experts predict continued technological growth in the future, making the importance and impact of RA stronger than ever before. Online shopping will revolutionize the way RAs are used to drive sales.

One gap I have identified in research is how sales associates can utilize RAs in stores to help drive sales. For example, iPads could be placed in dressing rooms to where shoppers could rate their clothing items on attributes such as fit and comfort and make recommendations in real time in stores.

The future of RA systems has many possibilities, many of which may not be conceivable. Although there are endless possibilities in the realm of RA systems, it will be important to remember that consumers cannot be overloaded with information or they may not make a quality decision (Xiao & Benbasat 2007).

Conclusion

In this paper I created a new method for organizing different components of the RA system into a process including inputs and algorithms, models and methods, outputs and results, and the future or RA systems. Most previous research has focused only on one or two of the following categories and very little research has been done on the entire process creating an overview and framework for RAs.

Inputs and algorithms can be broken into two main categories, content-based filtering and collaborative-based filtering. While both types of filtering can make a RA system more effective, I believe that collaborative filtering is more effective today. The number of online users has increased to where similar purchasers can be matched online to link up individual shoppers to provide more useful recommendations based on their similar peers. Specifically, memory-based filtering will be particularly useful as it further identifies new context and adopts the geographical nearest neighbor technique for the most useful community-based recommendations. The personalized scoring model provides an algorithm equation to determine how different online consumers match with one another.

RAs follow several models and methods, but one of the most important things to keep in mind is to not let the user blindly follow the recommendations presented. The co-clustering method effectively combines the content based filtering system with collaborative based filtering for more accurate results, but the trust and integrity of the system is at risk if a consumer believes a recommendation that is not a good fit. The distinction between “smart” and “knowledgeable” RAs help combat this trust issue. “Smart” RAs make the consumer aware of alternative options and facilitate learning. These are the best type of RA systems to maintain a consumer’s trust. However, “knowledgeable” RAs are less effective and just provide the best recommendation without any feedback. Consumers trust should be the most important factor when considering how to construct an effective RA system and creators should steer toward “smart” RAs that use a co-clustering method.

The outputs and results of RA systems deal with the level of product expertise, the trade-off transparency and the quality of choice. The results are what determine if the RA was effective. Product experts are hard to maintain trust in the RA system with because they are less likely to follow the recommendations, but rather fall back on their own knowledge.

A consumer who is presented with too many options will experience cognitive overload and will not be able to make a satisfying choice due to the trade-off transparency. Consumers are happiest with their quality of choice when there are few options presented and there is an explanation about why that product was recommended to them.

The future of RA systems could go in many directions. Research has looked at exploring implicit web browsing patterns, personality type indexes and the core reasons of why people continue to shop online in the first place, to avoid sales associates. I believe that the last point of research will be most important in the future. Although some have looked at making the online shopping experience just like you are in a store with a sales associate or live chat option available on the screen, many current online shoppers are trying to avoid just that, the nagging habits of sales associates.

In conclusion, I have developed a new framework that can be looked at to establish an effective RA system and identified strong components that make consumers gain trust in a system.

Appendix 1: Overview of RA Articles by Category

	Use	Characteristics	Impact	Transparency	Level of Product Expertise	Cognitive Cost Model	Trust in RA	Content Based Filtering	Collaborative Filtering	Case Study	Future of RA	Personality Types in RA	Effectiveness	Smart & Knowledgeable RA
Ahn & Park (2012)					X									
Charman-Anderson (2012)										X			X	
Chowhan, Deshmukh & Kolhe (2015)								X	X					
Gaughran (2013)				X			X	X		X				
Haubl & Trifts (2000)													X	
Henry (1980)					X								X	
Komiak & Benbasat (2004)							X							
Punj & Moore (2007)						X								X
Quan (2013)											X	X		
Shinde & Bag (2015)								X	X					
Swaminathan (2003)				X									X	
Titiriga (2011)				X					X					
Tseng & Lee (2015)									X					
Wang & Benbasat (2007)							X							
Wang & Benbasat (2005)								X						
Xiao & Benbasat (2007)	X	X	X	X			X	X	X				X	
Xu, Benbasat & Cenfetelli (2014)				X				X	X					
Zhu, et al. (2015)			X				X				X			
Zhu, Song & Zhang et al. (2008)									X					

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