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The Influence of Online Product Recommendations on Consumer Choice-Making Confidence, Effort, and Satisfaction

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THE INFLUENCE OF ONLINE PRODUCT RECOMMENDATIONS ON CONSUMER CHOICE-MAKING CONFIDENCE, EFFORT, AND SATISFACTION

by

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ABSTRACT

The number of products and services available online is growing at a tremendous pace. Consumers increasingly desire the ability to filter through the noise and quickly discover the products that are most relevant to their needs. Many businesses are implementing product recommender systems to provide this ability to consumers, and the result is often increased sales and more satisfied customers.

However, recommender systems can also have negative consequences for consumers. For example, a recommender system can bias consumers to purchase more expensive products. Additionally, theories of consumer choice-making suggest that recommender systems can sometimes make purchase choices more difficult, resulting in outcomes that are contrary to the intended purposes of the system, such as customers expending greater shopping effort and feeling less satisfied as a result of receiving too many suggestions.

The purpose of this dissertation is to further explore when recommender systems can negatively affect consumers' online shopping experiences. I investigate three research questions: 1) When do product recommendations increase, rather than decrease, shopping effort? 2) When do product recommendations decrease, rather than increase, shopping satisfaction? And 3) When do recommender systems decrease, rather than increase, consumers' choice-making confidence? I propose to study these questions by conducting an experiment using a fictitious retail website and online survey.

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DEDICATION

I dedicate this dissertation to my mother Mahin Shahbazi without whose constant love and encouragement I would not be where I am or who I am today.

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CHAPTER 1

INTRODUCTION

1.1 Recommender Systems

The emergence and mass adoption of computer technologies has led to rapid growth in the amount of information available to consumers. Through the internet, consumers have more information on goods and services, and simply more goods and services, available than ever before. However, some researchers argue that too much information can inhibit effective decision-making for both individuals and organizations (Edmunds and Morris 2000). For consumers, too much information, as a result of too many options, can make purchase choices more difficult and less satisfying (Bollen et al. 2010; Scheibehenne, Greifeneder, and Todd 2010; Schwartz 2016).

Intelligent computer agents have been suggested as a means of assisting consumers with making purchase decisions and discovering new brands. Essentially, these "agents" would operate in the form of automated systems that offer product or content suggestions to users based on their needs, preferences, and past behaviors as well those of other consumers. For example, many of the articles cited in this dissertation were discovered through Mendeley's "Suggest" feature, which recommends articles based those saved in one's library (**Figure 1-1**).

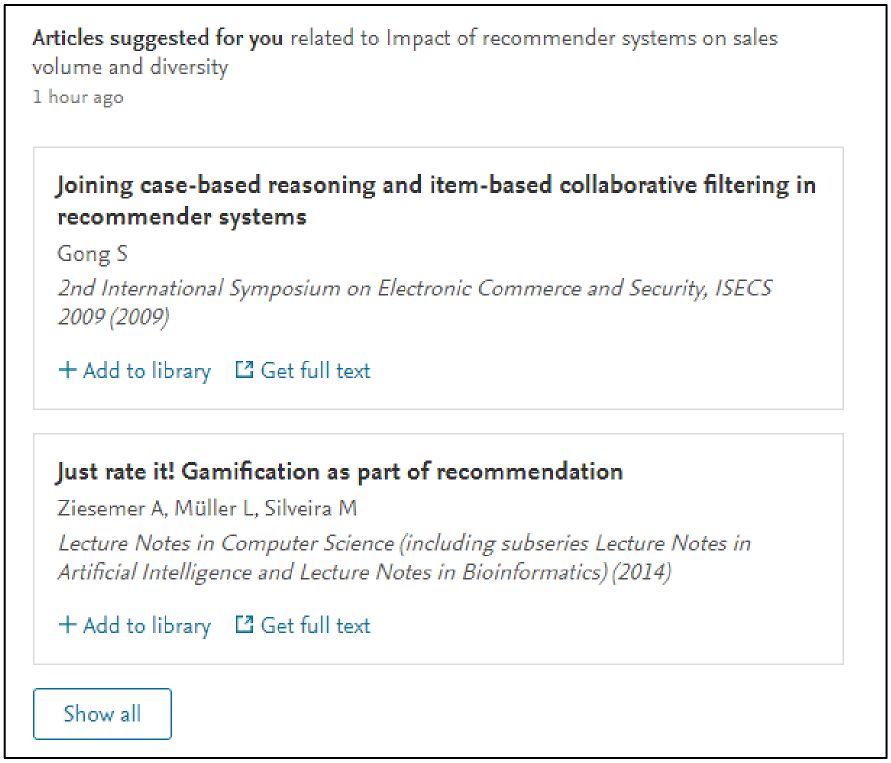

Figure 1-1: Suggestions by Mendeley's recommender system for scholarly articles.

Amazon, a pioneer in e-commerce, first implemented its automated product recommender system in 1998 to great effect; as much as 30% of Amazon's page views and 35% of their sales come from product recommendations (MacKenzie, Meyer, and Noble 2013; Smith and Linden 2017). For retailers seeking to implement a recommender system today, there exist many third-party solutions to choose from, including those from several big players like Amazon (Amazon 2020), Adobe (Adobe 2020), and IBM (IBM 2020). The widespread availability and effectiveness of recommender systems has led them to become a ubiquitous feature of retailers' websites.

Recommender systems are not only used to assist in product purchase decisions but have also become an integral part of many consumers' day-to-day activities. Whether browsing videos on YouTube, streaming music on Spotify, using Grammarly to help write an essay, or applying to credit cards through Credit Karma, consumers are depending on automated suggestions from these services to help them discover new content and make better decisions.

Recently, recommender systems have begun to more appropriately assume the role of intelligent computer agents via their integration with modern, machine-learning powered digital assistants. Consumer adoption of such assistants, like Apple's Siri, Amazon's Alexa, and the Google Assistant, is increasing; Amazon has sold more than 100 million Alexa devices (Bohn 2019) and consumers have made billions of dollars' worth of purchases via Alexa and other similar services (OC&C 2018). Consumers are coming to value these technologies because of their ability to assist them with daily tasks in a human-like manner, which includes recommending which actions to take and which products to buy (Stucke and Ezrachi 2017). For businesses, product recommendations via digital assistants are becoming a powerful way to engage consumers and proactively address their needs (Mierzejewski 2018).

Automated product recommendation systems are generally considered to be a positive development for both businesses and consumers. They can help consumers quickly discover interesting and relevant products while also increasing sales for businesses (Pathak et al. 2010; Smith and Linden 2017). However, businesses should take care when implementing recommender systems. A system that is not carefully designed can have unexpected or undesirable consequences for consumers. For example, when there are too many recommendations, making a choice can become more difficult (Bollen et al. 2010). When recommendations are presented with numerical attributes, consumers may be nudged towards choosing higher-priced products (Köcher et al. 2019). And when recommendations are based solely on the past sales and ratings of items, they can reinforce the popularity of already popular brands (reducing sales diversity), thereby making it less likely for consumers to discover niche brands or new entrants to the market (Fleder and Hosanagar 2009; Lee and Hosanagar 2019). Recommender systems generally drive more sales for retailers, but to understand why those sales occur and how brands are affected, retailers should carefully consider how different aspects of the system affect different types consumers. Additionally, retailers should consider if their goals in implementing the system are consist with the goals of their customers. Alignment of recommender goals with customers goals results in a system that produces the greatest value for all parties.

Automated product recommendations are a great convenience for consumers, but they are not always effective at facilitating a better customer experience. In fact, some research suggests that recommender systems can sometimes be detrimental to the customer experience. Thus, marketing and information systems researchers have called for more research investigating when recommender systems may result in outcomes that are not in consumers' best interests (Xiao and Benbasat 2018; Zhao et al. 2018).

1.2 Outcomes of Recommender Systems Use

The outcomes of recommender systems can be examined at the consumer-level (e.g., customers' shopping time) and at the business/market-level (e.g., sales volume and diversity) (Zhao et al. 2018). Effects that may initially seem beneficial can result in undesirable long-term consumer- and market-level effects. For example, services such as YouTube and Facebook provide their users with an endless stream of content suggestions, which has increased user engagement and overall revenue for the platforms, but has also contributed to the internet addiction many consumers suffer from (Balakrishnan and Griffiths 2017; Kittinger, Correia, and Irons 2012).

Marketing scholars have long emphasized placing consumer well-being at the forefront of marketing efforts (Dawson 1971; Lunde 2018). Now, both YouTube and Facebook are actively taking steps to help users control and reduce the amount of ‘wasted’ time they spend on their platforms (Lyn Pesce 2018). Another example of potentially unintentional (or accidental) effects, more relevant to tangible product recommendations, is increased price competition between firms (Ghoshal, Kumar, and Mookerjee 2015). Additionally, the potential for exerting market control via recommender systems may incentivize businesses to engage in unethical or anticompetitive practices relating to product pricing, consumer privacy, and consumer choice (Gal and Elkin-Koren 2017; Gal 2017; Stucke and Ezrachi 2017).

Whether recommender systems provide consumers with shopping experiences that are desirable from their perspective depends on how the recommendations are generated and presented (i.e. the design characteristics of the system. The design characteristics of recommender systems are proposed to influence several important outcomes related to consumer choice-making such as choice effort, choice strategy, choice confidence, and product evaluations (Xiao and Benbasat 2007, 2014).

1.3 Characteristics of Recommender Systems

Recommender system characteristics fall into two categories: those related recommendation generation and those related to recommendation presentation (**Table 1-1**). The characteristics of recommendation generation are those that guide the system in determining what items to recommend. These are (1) the type of data used by the system,

(2) the algorithms used, (3) the criteria for recommending a product, and (4) how the user can interact with the system to influence future recommendations. The characteristics of recommendation presentation are those that specify (1) what information is presented alongside recommended items, (2) how often new recommendations are provided, (3) how many recommendations are simultaneously presented to the user, and (4) at what stages of the shopping process recommendations are provided, and.

Both types of characteristics interact to determine how the system influences consumer choice. The characteristics of recommendation generation influence what items (products/brands/sites) the user will see. The characteristics of recommendation presentation influence how they will see those items. Both types of characteristics interact to influence purchase behavior. Researchers should consider how specific characteristics interact to influence users so that systems that can be more predictably employed (i.e., avoiding pitfalls for consumers and brands).

Table 1-1: The design characteristics of Recommender Systems.

Recommendation Generation	Recommendation Presentation
1. Data Type	1. Information Provided
2. Algorithms	2. Recommendation Frequency
3. Recommendation Criteria	3. Recommendation Quantity
4. User Interaction	4. Shopping Stage

1.3.1 Recommendation Generation

Not all of the design characteristics shown in **Table 1-1** are completely independent of each other. A design decision in regard to one characteristic will influence decisions made regarding the other characteristics of the system. For example, the choice of algorithm will require the choosing of certain data types. In general, there are three classes of data that a recommender system can use: data that characterizes the item, data that characterizes the user, and data that characterizes the interaction between user and items within the system (**Figure 1-2**). Item characterization data is the data that specifies the item's properties, such as its brand, category, and price. User characterization data is the data that specifies the user's properties, such as their location, demographics, interests, habits, intents, and context. User-item interaction data consist of the user's past behavior with items in the system, such as item views, purchases, and ratings.

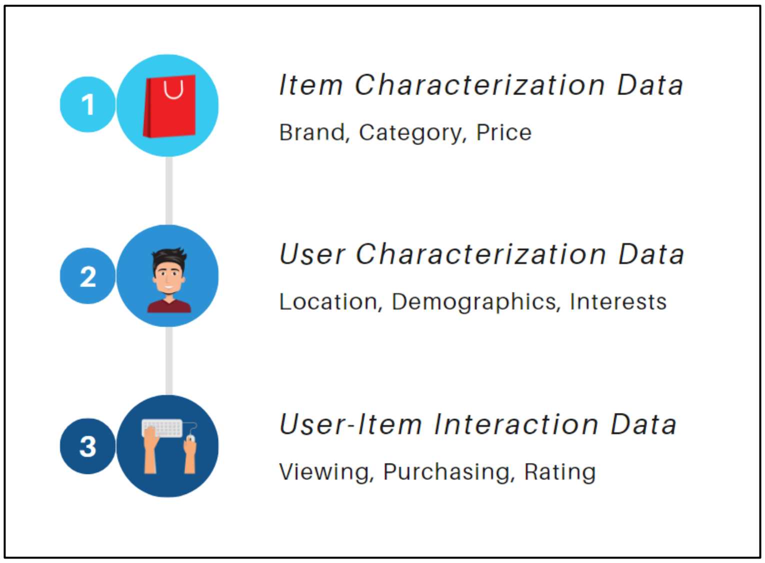

Figure 1-2: The three classes of data used by recommender systems.

The literature often mentions two data types used by recommender systems: explicit and implicit feedback. These types of feedback are used to identify what items the user is interested in. For example, a movie streaming service can explicitly infer a user was interested in a movie from a numerical rating given to that movie by the user, or, the system can implicitly infer that the user was interested if they watched the movie, and then recommend similar movies (Google 2020a). Explicit feedback equates to the user explicitly saying "Yes, I am interested in this," whereas implicit feedback consists of those user actions and data points that the system uses to infer user interest. User characterization data and user-item interaction data can both consist of implicit and explicit feedback. For example, a user can explicitly specify their interests by selecting from a list of predetermined categories when prompted or by rating an item (**Figure 1-3**), or the system can use the user's location data and item viewing history as implicit feedback inputs to identify their interests.

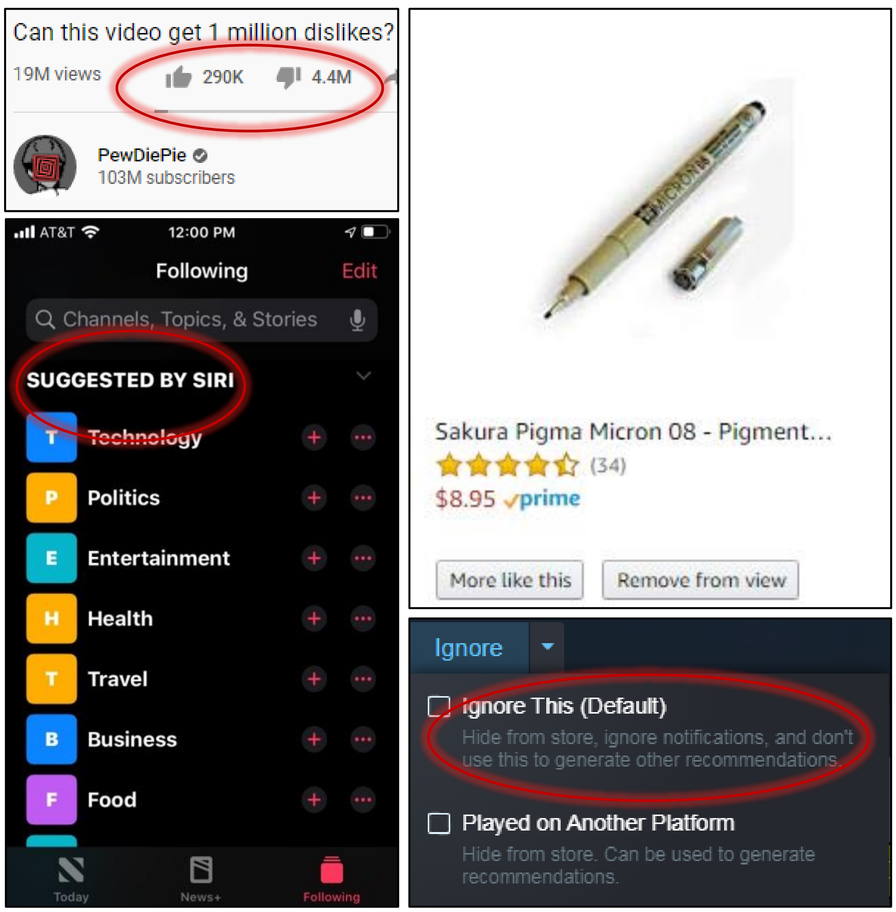

Figure 1-3: Users can explicitly state their interests by selecting from predetermined categories (shown bottom left Apple News), rating/liking an item (shown top left YouTube), requesting suggestions similar to an item (shown bottom middle Amazon), or rejecting suggestions similar to an item (shown bottom right Steam).

Two commonly discussed families of algorithms for generating recommendations are content-based filtering and collaborative filtering. “Content-based filtering uses item features to recommend other items similar to what the user likes, based on their previous actions or explicit feedback” (Google 2020b). This approach relies on two types of data: item data and user-item interaction data. For example, if a user on Amazon visits product pages for party games, he will be recommended similar types of party games (**Figure 1-4**).

Collaborative filtering, like content-based filtering, also uses item data and user-item interaction data, but groups users together based on similarities in taste (liking or purchasing the same or similar items). In other words, it “uses similarities between users and items simultaneously to provide recommendations” (Google 2020a). With this approach, if User A and User B both purchased the same item in the past, and User B goes on to purchase an unrelated item, then User A may be recommended that same item (**Figure 1-4**). In this way, User A receives recommendations that are not necessarily similar to his past purchases, which allows him to discover items a greater variety of items. The most sophisticated systems use a hybrid approach to recommendation generation, which combines the results of content-based filtering, collaborative filtering, and other approaches.

In addition to using item data and user-item interaction data, content-based and collaborative filtering can both also involve the use of data characterizing the user, such as their age and location; however, this is not required. For example, Netflix does not use age or gender as inputs to its recommendation algorithm (Netflix 2020). Other approaches to product recommendation may not involve any user related data at all, such as items hand-picked by experts for select product categories, or use only aggregate user data, such as a firm showcasing its most viewed products (**Figure 1-5**). In contrast to approaches that generate recommendations for individuals or select groups, such recommendations can be labeled as non-personalized. In the case of a new user on whom there is little to no data (i.e., the cold start problem), a recommender system may initially provide non-personalized recommendations until more data is collected.

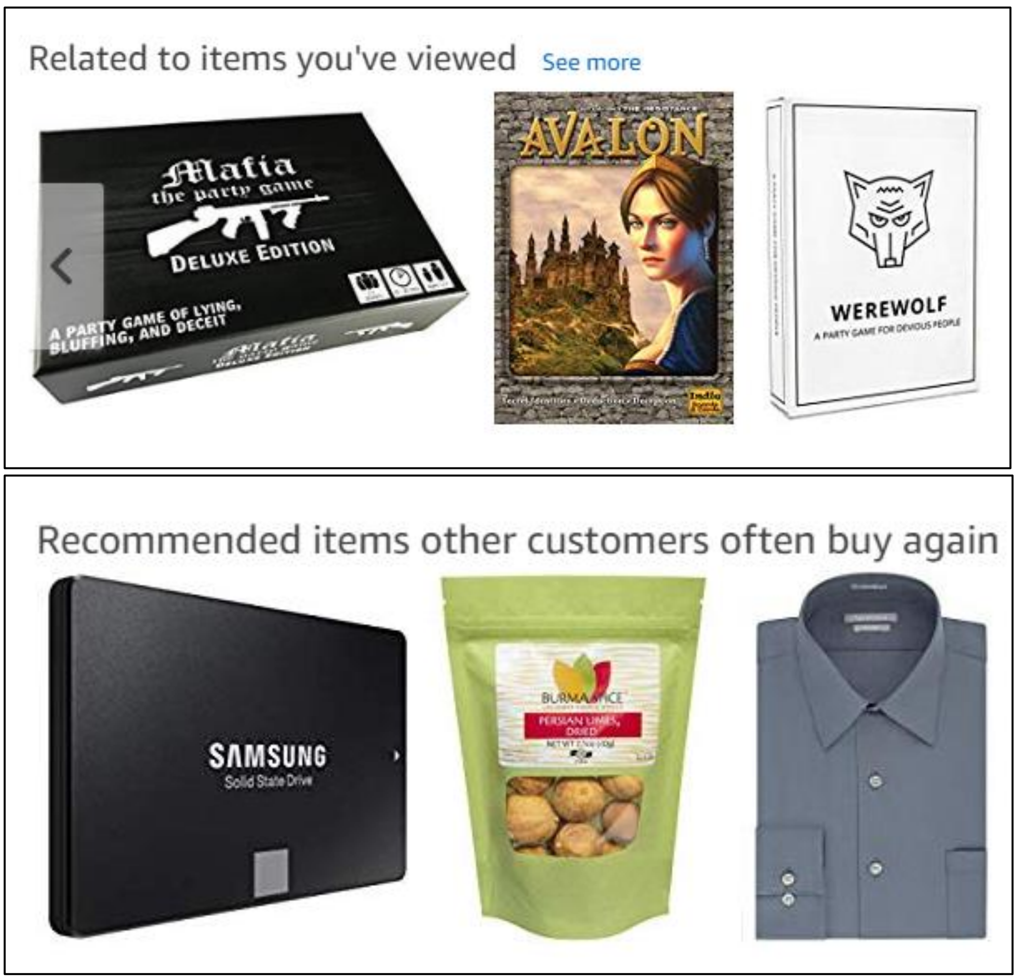

Figure 1-4: Personalized product recommendations from Amazon generated by content-based filtering (shown top) and collaborative filtering (shown bottom).

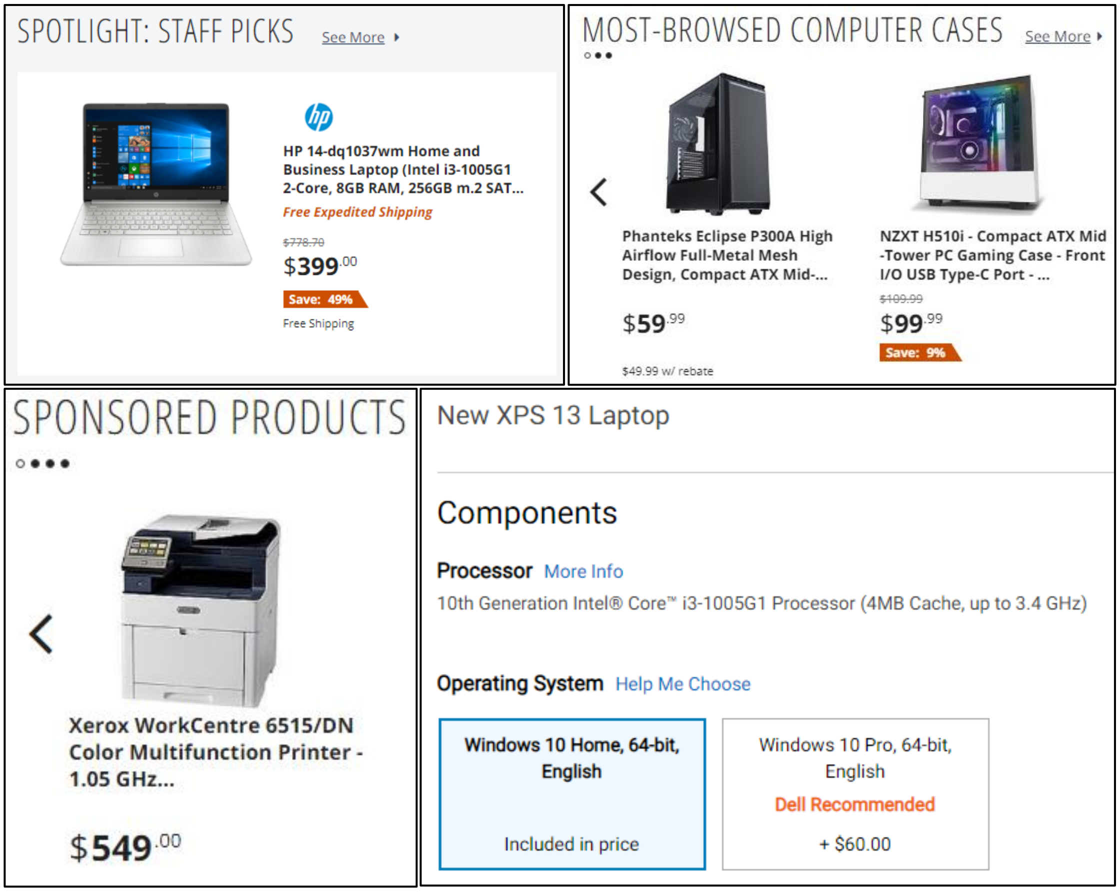

Figure 1-5: Non-personalized product recommendations from Newegg.com (shown top left, top right, and bottom left) and Dell (shown bottom right).

A system must have some criterion for recommending the items it does. This criterion often reflects a similarity between items and users. Once a certain similarity threshold is passed the item may be recommended. But how is the similarity between items and users determined? Both content-based and collaborative filtering approaches use embedding vectors in an embedding space that captures some latent structure of the item or user set. These vectors are used as inputs to measure the similarity between items and users. Most recommender systems rely on one or more of the following three approaches to calculating similarity: the cosign of the angle between two vectors, the dot product of two vectors, and the Euclidean distance (Google 2020c). The measure of similarity used must be chosen with care as it can influence how often already popular or rare items are shown.

In addition to similarity criteria, advanced recommender systems use a machine learning model to score and rank the recommendations generated to select the best set of items to display (Google 2020d). However, the machine learning objective that is implemented can negatively affect the quality of the recommendations if it is not carefully selected. For example, if the model is given the objective of maximizing watch time, the scoring model could become biased towards recommending very long videos. Additionally, the scoring model could take order effects into consideration (e.g., items that appear lower in a list or on the screen as less likely to be clicked), however this may currently be too computationally expensive for some applications (i.e., it is not feasible for the model to consider all possible positions for a given item).

Lastly, users can be provided with explicit options to influence the recommendations they receive. These options include allowing the user to specify what information is used to generate the recommendations or even to delete their user data history (**Figure 1-6**). The options for specifying recommendations will be unique to each system, but one feature that many systems have in common is allowing users to rate items.

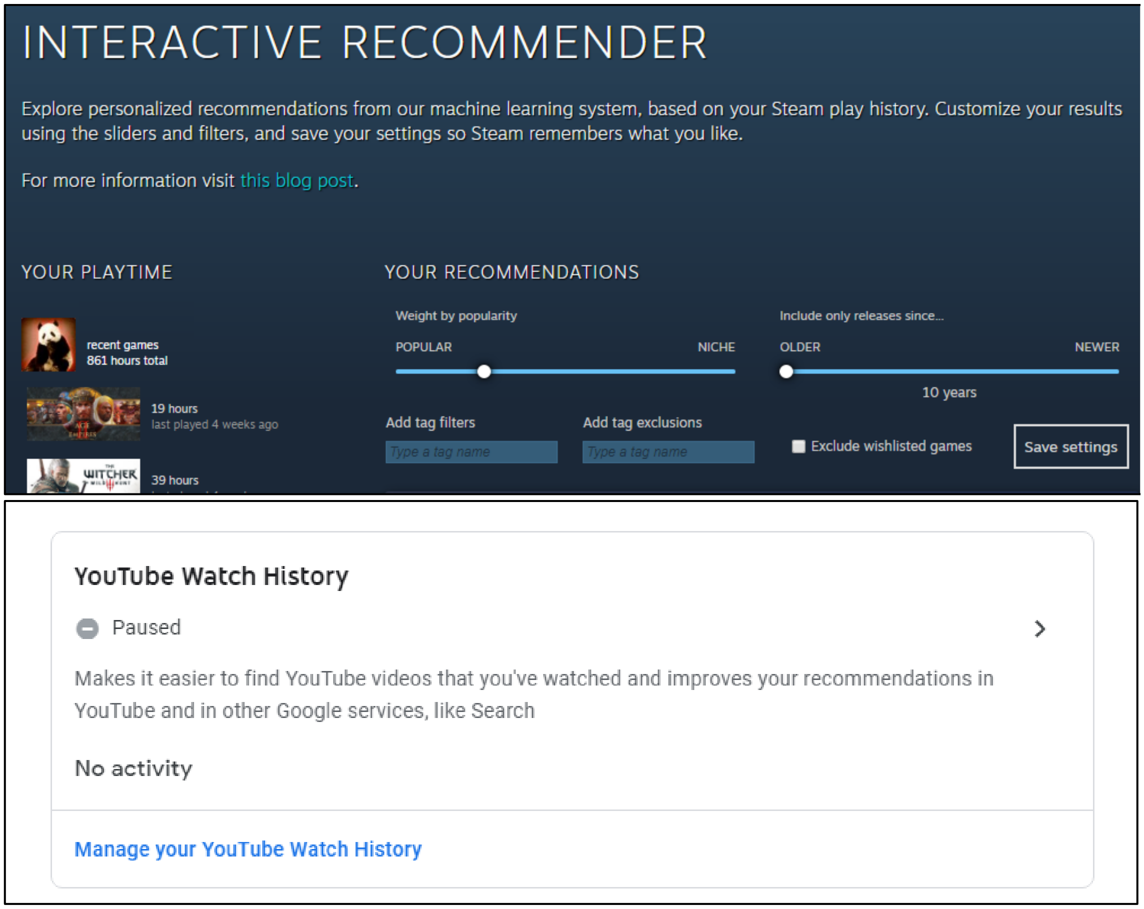

Figure 1-6: Steam (store.steampowered.com) provides options for users to specify what video game recommendations they receive (shown top). Google provides options for users to manage their data, which impacts their recommendations across Google's services (shown bottom).

1.3.2 Recommendation Presentation

Recommendations are displayed to users with information about the item and often also with information about how other users have interacted with it, such as the item's rating. The title of the item, its rating, its views, its image, its price, its attributes, and why it is being displayed are all potential pieces of information that can be included (**Figure 1-7**). These pieces of information all influence whether a user will click a recommended item and their subsequent purchase choice. For example, a recent study found that the numerical attributes of recommended products can bias consumers to view and purchase higher priced products through an anchoring effect (Köcher et al. 2019). These effects were observed in both experimental studies and real customer data from a large European retailer.

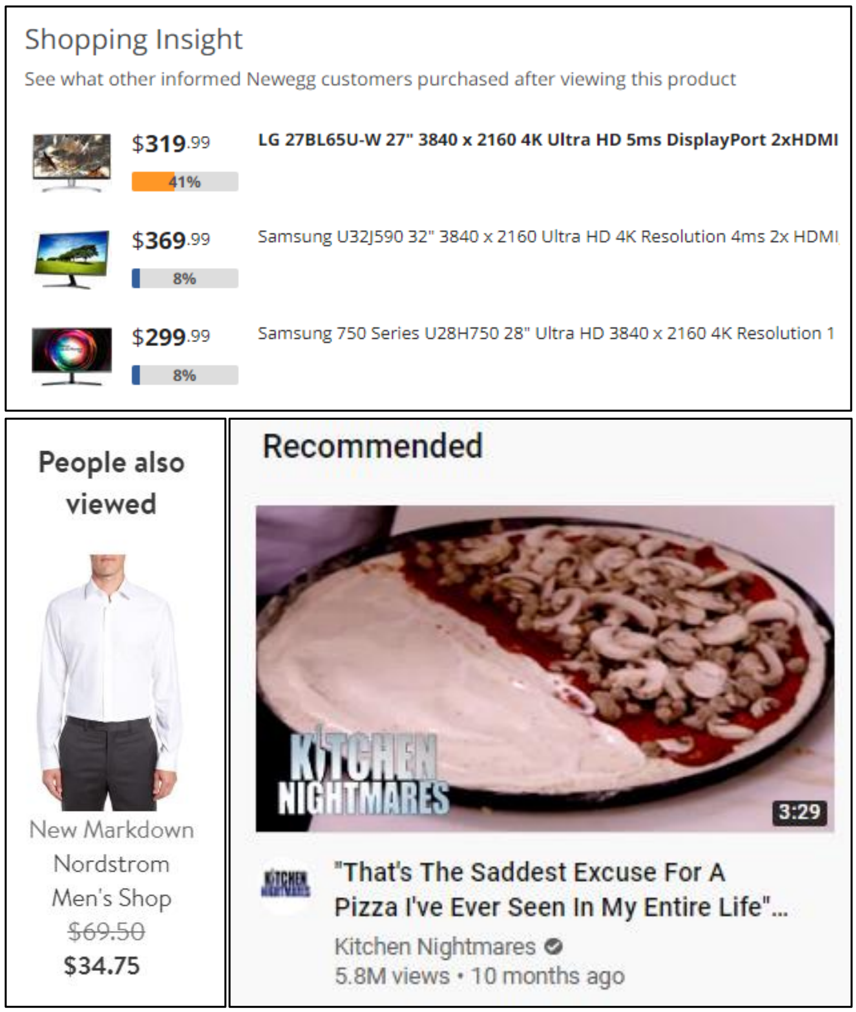

Figure 1-7: Recommendations with (shown top Newegg; shown bottom left Nordstrom) and without (shown bottom right YouTube) information about why the item was displayed to the user.

The frequency at which new recommendations are provided to users can vary from page to page on a website. For example, Amazon presents new recommendations every time its homepage is refreshed, but recommendations on product pages are updated less frequently. A closely related characteristic is the quantity of recommendations simultaneously presented to the user. A preset number of recommendations can be available for the user to view, as on the Amazon or Newegg homepages, or the user can scroll endlessly to continue viewing more recommendations, such as on the YouTube and Steam (store.steampowered.com) homepages, though this typically occurs for users who are signed in to the website. As with recommendation frequency, the quantity of recommendations can also vary from page to page on a website, and even within a single page under sections for different types of recommendations. Few studies on recommender system have examined how the quantity of recommendations can influence choice-making; however, there do exist many of studies on how the quantity of alternatives influences choice-making in other contexts (Scheibehenne, Greifeneder, and Todd 2010).

Lastly, recommendations can be presented to users at any stage of the shopping process. There are many perspectives on what the shopping process, or buyer/consumer journey, entails, but essentially they all describe a stage of awareness, a stage of interest, a stage of desire, and a stage of action; these four stages are commonly referred to as the AIDA model. Awareness describes a stage where the consumer has become aware of the category, product, or brand, but is not actively seeking to purchase or consume it. Interest indicates a stage where the consumer is considering the category, product, or brand as an alternative for future purchase or consumption choices. Desire is the stage where the consumer has a favorable disposition towards purchasing or consuming a specific category, product, or brand. Finally, action describes a stage where the consumer finally makes the purchase or consumption choice, and potentially takes other actions such as leaving a review. Consumers do not always go through all the stages in a linear fashion; they may not even pass through all four before making a purchase or consumption choice.

The function of a recommender system is to present users with suggestions. Suggestions can be presented while the consumer is at the Awareness, Interest, Desire, and Action stages for any particular item, and can stimulate awareness, interest, desire, and action for the new items, sending the consumer on new journeys. An online retailer can provide suggests on different sections of their website that correspond to the various stages of the shopping process. These include the homepage, a product page, the checkout page, account page, or another page dedicated to providing suggestions. There are other means an online retailer can use to provide suggestions too, such as mobile notifications and email **Figure 1-8**. Ultimately, recommender systems can be used to guide consumers at all stages of their buyer’s journey.

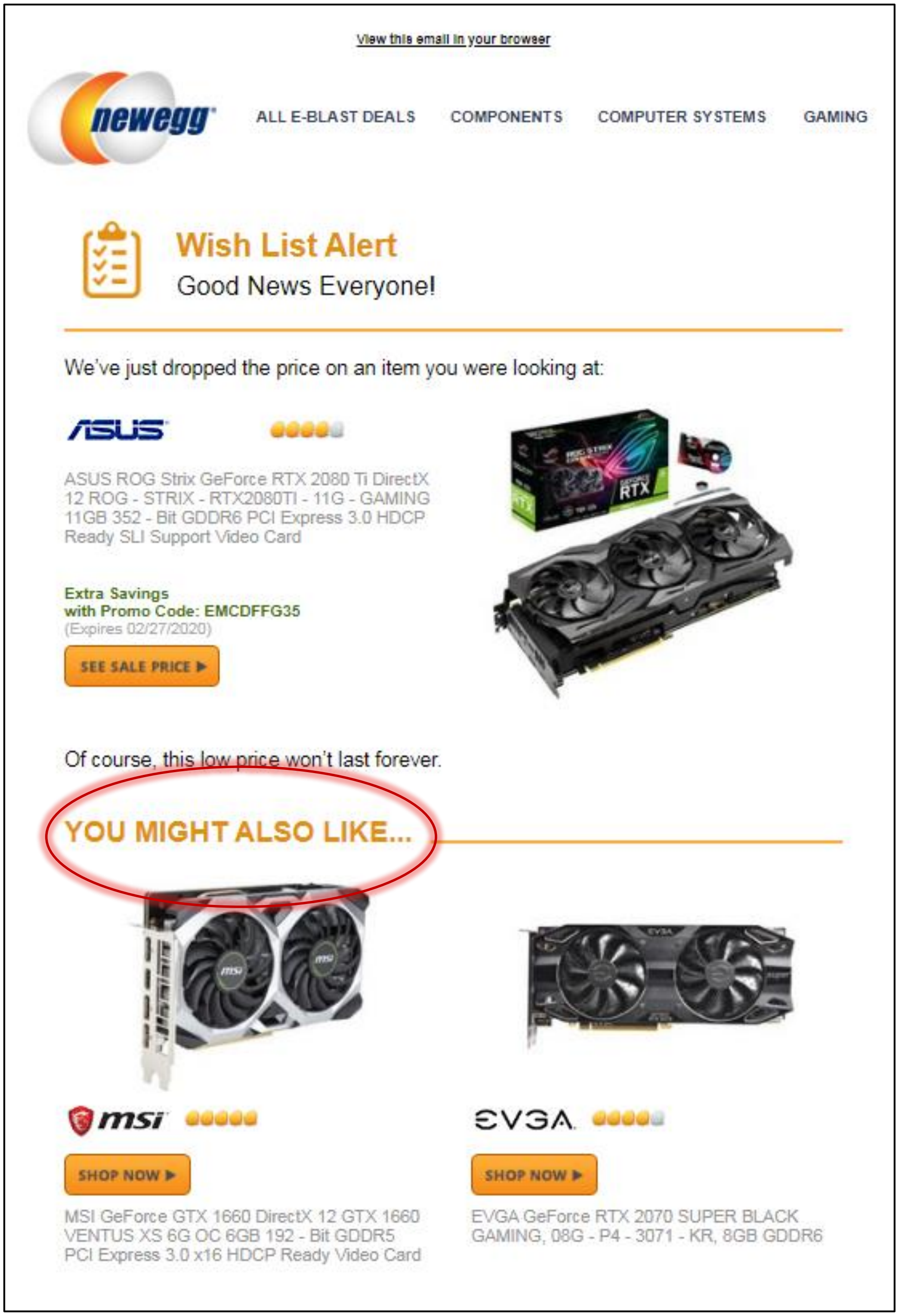

Figure 1-8: Recommendations in an email from Newegg. The consumer was at the desire stage for the ASUS product and added it to his wish list. The recommendations in the email serve to stimulate awareness of and interest in the MSI and EVGA products.

1.4 Choice-Making and Recommender Systems

User focused recommender research has investigated a number of outcomes related to choice-making. These include effort, strategy, confidence, rating, purchase behavior, click through rate, time spent on page, and satisfaction.

1.4.1 Effort

The fundamental assumption driving the development of recommender systems is that they lead to greater convenience for the customer. Convenience often ranks high in importance amongst consumers when determining where to shop and is a strong predictor of customer loyalty (Jiang, Yang, and Jun 2013). Online stores strive to give consumers greater convenience by providing them with more information, choices, and means of discovering the products that they would like to purchase in less time, all of which can be facilitated by recommender systems. A successful recommender system should ultimately be designed to help users explore new ideas and help businesses increase sales (van Capelleveen et al. 2019).

Recommender systems create convenience by making it easier for customers to quickly find products that they would be interested in. But what if the system helps the customer find too many of the products they like? Although the research is mixed, many scholars argue that too many options results in choice overload, which has been associated with negative outcomes for the consumer (Schwartz 2016). Recommenders are often designed to make many recommendations to consumers, either by presenting them with the option to endlessly scroll through more recommendations, or by regularly notifying the customer of new recommendations. If it is true that these systems are overloading consumers with too many choices, then they may have inadvertently brought the consumer back to square one in terms convenience. Recommenders may make it harder for the customer to make a choice by presenting them with too many options they are interested in, which could result in them expending greater effort to make a satisfactory decision.

Most studies suggest that product recommendations are effective in reducing the amount effort customers expend to find their desired product. Effort can be measured by the extent of product search (e.g., number of products viewed) (Xiao and Benbasat 2018), decision time (Huseynov, Huseynov, and Özkan 2016), or perceived cognitive effort (Xiao and Benbasat 2018). However, recommender systems are not always effective at reducing effort or can even have the opposite effect (Bollen et al. 2010).

Broniarczyk and Griffin (2014) review the impact of two key factors of what they term “consumer empowerment” (choice freedom and expansion of information) on the choice difficult consumers experience in today’s shopping environment. Their review reveals “that though these two consumer empowerment factors offer numerous potential benefits, they also can magnify such sources of decision difficulty as task complexity, tradeoff difficulty, and preference uncertainty” (Broniarczyk and Griffin 2014, p. 608). Several key variables were found to moderate these effects of consumer empowerment on choice difficulty: consumer knowledge, mental representation, maximization tendency, information type, and information organization. Interestingly, they also review the benefits and potential pitfalls various decision aids, including recommenders, and find that they are not all effective at simplifying decision making. For example, one of the reviewed studies show that “decisions aids that provided a simple overall star evaluative rating but no a detailed information matrix on each alternative increased decision satisfaction among low knowledge consumers by reducing perceived task difficulty"(Broniarczyk and Griffin 2014, p. 620). Surmising the potential pitfalls of recommendations, Broniarczyk and Griffin (2014) caution that recommendations can create difficulty if the recommendation conflicts with a dominant option or a consumer's preferred option and that lowered search costs may lead to over-search and worse choices for maximizing consumers.

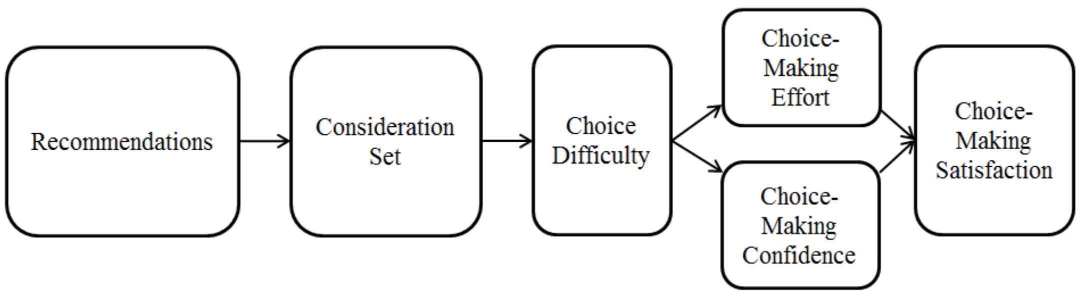

Figure 1-9: A conceptual model of how recommender systems could affect important consumer choice-making outcomes: effort, confidence, and satisfaction.

1.4.2 Confidence

A second major assumption driving recommender systems development is that often the consumer is not sure about what they want because they do not have much experience in the product domain or purchase process. This is often true and consumers usually want some assurance that they are making the right choice, whether that assurance comes from family, friends, colleagues, experts, or computer models. In other words, consumers always want to feel more confident in their ability to choose. By explaining to the customer why an item is recommended, a recommender system may provide them with this assurance. However, the confidence from gained from assurance only comes when the user has confidence in the system, which partly involves trust in the system and seller. A recent study has indicated that consumers are more likely to take advice from an algorithm than from a human (Logg, Minson, and Moore 2019). This effect may carry over to taking advice from a recommender system, which use algorithms to advice consumers on purchase decisions amongst many other things.

However, some studies show that consumers do not always trust recommenders (Yoo and Gretzel 2008). Essentially, what is suggested by these studies is that consumers will follow the advice of a recommender when they have confidence in it. But that does not mean they have confidence in themselves. Actually, it would suggest the opposite: recommendations are more likely to be followed by consumers who have less confidence in their own ability to make the most satisfying choice. In the experiments by Logg, Minson, and Moore (2019), lay people were found to adhere more to advice when they thought it came from an algorithm than experts were.

Confidence in choice-making may be observed as a general personality trait or vary between purchase situations across domains. In a purchase situation, such as wine selection, confidence may manifest as perceived purchase risk and purchase anxiety (Barber, Almanza, and Dodd 2008). Customers who are inexperienced and less familiar with the product type, or even purchase process, might be less confident that they made the best decision (Park and Lessig 1981; Swaminathan 2003), but confidence in choice could also depend on how expensive the product is (perhaps when the perceived financial risk is high (Swaminathan 2003)) and the credibility of the recommender system (Yoo and Gretzel 2008).

Can the recommender system itself reduce the customer's confidence in their own ability? In other words, can customer who would otherwise be confident in their decision making be conditioned to trust a system more when presented with a recommendation?

As illustrated through this chapter, recommendation systems are being implemented in almost all computer-based activities and services used by the majority of the population in developed countries. How are these systems conditioning the minds of consumers?

Researchers have shown that the brain physically changes in response to any activity and inactivity over a prolonged period of time. These changes can be caused from the outside-in, for example, by television viewing altering the grey matter in children's brains (Takeuchi et al. 2015), and from the inside-out, for example, by meditation increasing thickness is certain parts of the brain (Lazar et al. 2005). The brain gets better at the things it does often, and its capacity for things that are not done often diminish. If consumers are not exercising their faculty for making choices on their own, without assurances, they may begin to lose their capacity for effectively doing so, or maybe just start feeling less confident about doing so. The results of one study suggests that search engines, such as Google, are shifting people's learning strategies and reducing their motivation, or perhaps even ability, to remember information – subjects "were better at remembering where the information was stored rather than the information itself" (Bohannon 2011).

Such an observation (that external information storage affects memory) is not completely new. The Roman emperor Julius Caesar commented that the clergymen of the Gauls (peoples native to western Europe) chose not to write down their laws and customs, only passing them down by oral communication: "Reports say that in the schools of the druids they learn by heart a great number of verses… They do not think it proper to commit these utterances to writing... I believe that they that they have adopted these practices for two reasons: they do not wish the rule to become common property nor those who learn the rule to rely on writing and so neglect the cultivation of memory… it does usually happen that the assistance of writing tends to relax the diligence of the student in the action of the memory" (Loeb 1917, p. 339). Socrates, who did not write anything down himself, may have also shared in this belief (LeBlanc 2013).

The invention of writing is also the invention of external information storage and retrieval systems, which includes search systems. Possibly then, writing and search systems affect memory and learning strategies in similar manners; the person adopts the path of least resistance and remembers what and where to search rather than remembering the information itself.

The effects of recommender systems, which involve information storage and retrieval, on memory have not been studied, but recommender systems have been found affect choice-making experiences and strategy (van Capelleveen et al. 2019). For example, recommender systems can influence the size of the user's consideration set (Goodman et al. 2013). Goodman et al. (2013) conducted research on whether recommendation signage (e.g., "Best Seller", "Award Winner") helps or hinders consumers faced with choosing from large product assortments. Across three experiments they found support for the hypothesis that consumers with more developed preferences formed larger consideration sets and experienced more choice difficulty: the recommendation signage created a preference conflict within the consumers. Incidentally, consideration sets can also influenced by memory (Alba, Hutchinson, and Lynch 1991). In fact, memory, the ability to recall product information and past decisions, plays a significant role in consumer choice-making (Alba, Hutchinson, and Lynch 1991).

There are two possible paths by which a recommender system may reduce confidence in a user's own ability to make the most satisfying choice. One is by a shift in choice-strategy adopted by the user in response to the system: the user defers to the system, which is perceived as more expert – an act which may validate the user's belief in their lack of ability. The other is by presenting too many recommendations (potentially all desirable and of interest to the consumer) and influencing the user's consideration set such that the user has trouble weighing the options and thus feels less sure about their ability.

There is not much research available that clearly supports the former path. In fact, one study showed the opposite: people's confidence in their ability (making scientific knowledge claims) was increased after exposure expert information (Scharrer et al. 2017). Possibly then, knowledge from a perceived expert, person or algorithm, increases confidence in one's own abilities, but this does not necessarily translate to enhanced skills. The second path by which recommenders can negatively influence confidence – that confidence can be reduced as a result of a larger consideration set size and thus greater uncertainty about preference – seems more likely, or at least is supported by some previous research.

Increased consideration sets have been linked to choice difficulty (Goodman et al. 2013). Tsai and McGill (2011) explore how the difficulty of a task, manipulated by manipulating processing fluency, influences choice confidence through the lens of construal level theory. They find that "when consumers adopt a low-level construal, which highlights the feasibility of a target event, such as the *how* aspects involved in making a choice, fluency increased confidence. However, when consumers adopt a high-level construal, which highlights the desirability of the same target event, such as the *why* aspect or the benefits of purchasing a product, fluency decreases confidence" (Tsai and McGill 2011, pp. 807-808). These findings are in line with those of Broniarczyk and Griffin (2014) who identify decision difficulty with information and preference uncertainty. Usually, uncertainty is a sign of lesser confidence.

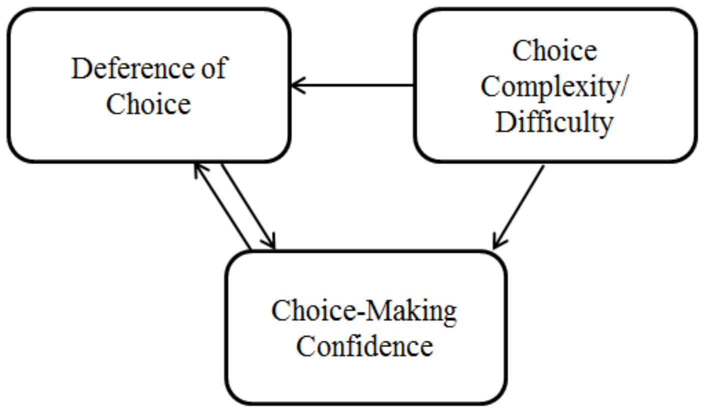

Figure 1-10: Potential paths through which recommender systems may influence choice-making confidence: choice complexity/difficulty to confidence and deference of choice to confidence.

The telos of marketing is to maximize customer satisfaction. The paradox of choice theory suggest customers are satisfied with less options, not more. However, the prevailing view in customer relationship management is to push toward personalization and convenience, which means having more options available for more types of customers, and this can be facilitated most efficiently with a recommender system. The two perspectives would suggest that a balance needs to be struck between personalization and the number of options presented by a recommender, even when many options would be desirable to the consumer. Can there too many recommendations? When are effort, confidence, and satisfaction negatively impacted by recommendations, if at all, and under what conditions and for what customers?

1.5 Purpose of Dissertation

The purpose of this dissertation is to better understand how automated product recommendations impact consumers' online shopping experience in a potentially negative way. The research conducted herein will explore three questions regarding the detrimental effects of recommender systems on the customer shopping experience: (1) When do recommender systems decrease, rather than increase, consumers' choice-making confidence? (2) When do product recommendations increase, rather than decrease, shopping effort? And (3) When do product recommendations decrease, rather than increase, shopping satisfaction?

More specifically, the study will investigate if and why the presence of product recommendations changes the amount of time consumers take to make a purchase choice, their level of satisfaction with various aspects of the shopping experience, and the level of efficacy they feel they have in their ability to make the best choice. To investigate these outcomes, I propose to conduct an experiment using a fictitious retail website, to create a simulated shopping experience, and an online survey.

1.6 Contributions of the Research

This study provides several important contributions for marketing theory, research, and practice. Firstly, is the literature review that surmises and comments on prior comprehensive reviews of recommender systems applications and how they influence choice-making strategies. Recommender systems are a hot research area with not only thousands of empirical articles published but many review articles as well. The synthesis of reviews presented here gives an overview of essential concepts related to the application, design, and evaluation of recommender systems. These include the consumption domains to which recommenders are being applied, techniques for generating recommendations, and consumer choice-making patterns among other things. Such a review will be helpful for academics and designers looking for a foundational understanding in recommender system design in relation to how they are applied and influence consumer choice. Much of marketing practice and research is occurring in digital settings. Both researchers can practitioners, even those outside of recommender systems research, can benefit from the review and research presented here – the generalizations for choice-making theory likely carries over to other purchase situations.

Additionally, research on choice difficulty, confidence, effort, and satisfaction are reviewed. Findings from the reviewed empirical articles server to inform designers and researchers on best practices for recommenders in a variety of shopping situations. Understanding how recommenders after shopping experiences and purchase decisions in not only important for a business striving to meet its financial goals, but also consumer researchers studying choice. Whether designing a selection of choices for an e-commerce page or for a research project, understanding how choice-making is influences by recommendations is essential for interpreting any observed effects. With this understanding, businesses can avoid any unintended effects, whether for the customer experience or the organization's bottom line, from implementing a recommender system. Specifically, this study contributes to an understanding on when recommenders make choices more difficult or less satisfying – the opposite of their intended purpose.

Lastly, the methodology employed in this study involves the collection of observed and self-reported data. This is accomplished through an experiment which involves the combination of a website, which tracks user behavior, and survey, which captures user beliefs and attitudes. The experiment explores the relationship between recommendations and choice difficulty and contributes to the literature on choice-making and information overload. The methodology provided here can server as a template for any number of future recommender research projects.

1.7 Organization of the Study

Chapter 1 provides an overview of the prevalence of recommender systems in consumer's day-to-day experiences and the main characteristics of recommenders that could influence choice. Furthermore, it comments on how recommenders might affect choice-making effort and confidence, explains the purpose of the study, and contributions of the research. Chapter 2 synthesizes prior reviews on recommender systems applications, techniques for recommendation generation, how recommenders influence choice-making strategies, and what aspects should be considered when assessing recommender performance. Chapter 2 also provides background on choice freedom and decision difficulty and reviews empirical studies on recommenders and choice-making effort, confidence, and satisfaction to build a research model that is explored using the experiment described in Chapter 3. Chapter 3 explains the experiment in detail, describing the conditions subjects will experience, the measures that will be taken, and the analyses that will be carried out to explore the research questions. Chapter 4 reports the characteristics of the subjects and the results of the analyses. Chapter 5 presents an interpretation of the results and the implications for recommender systems design. Chapter 6 closes this dissertation by summarizing the contributions of the study and commenting on future research directions.

CHAPTER 2

BACKGROUND

2.1 Recommender Systems Applications and Design

2.1.1 Application Domains

RECOMMENDER CLASSIFICATIONS

Since the mid-1990s recommender systems have become an important field of research for computer science, information systems, and marketing. Of these three fields, marketing has the least number of publications on recommender systems. However, as illustrated in chapter 1, these systems are becoming an integral part of the marketing effort for many online businesses and services. Advancements in computer and internet technology have allowed recommender systems to be implemented effectively in a variety of consumption contexts for a variety of products and services. Several articles have attempted to review and categorize the literature on recommender systems according to their application domain and methods for generating recommendations. A review of these articles will be instructive for understanding the scope of recommender systems applications and how different systems aid consumer decision making in different contexts.

Park et al. (2012) review recommendation systems research published in academic journals between 2001 and 2010. Their review examined the distribution of 210 articles from 46 journals by year of publication and classified those articles according to the data-mining techniques and field of application studied in each one. Their classification framework consists of eight application fields and eight data-mining techniques and builds off prior research by Schafer et al. (2001), who reviews the application of recommender systems in e-commerce contexts to develop a taxonomy of recommender systems.

Schafer et al. (2001) posit that traditional marketing methods have laid a bedrock foundation for the growth of recommender systems as a marketing tool. They view recommender systems as an application of data mining that has evolved in response to market conditions that facilitate an ever-increasing set of choices in products to buy and information to consume. These conditions created challenges for retailers who struggled to provide the level of support needed to help customers make the most satisfying choices. An integration of database marketing, targeted advertising, and recommender systems has evolved to help retailers meet the challenge of suggesting the right products to the right consumers.

Schafer et al. (2001) argue that recommender systems enhance e-commerce sales by three means:

(1) Converting browsers into buyers

(2) Increasing cross-sell

(3) Building loyalty

They provide six examples of e-commerce sites specializing in different types of products (Amazon, eBay, CDNOW.com, Drugstore.com, MovieFinder.com, and Reel.com) that have benefited from recommender systems the three aforementioned ways. Shafer et al. (2001) proceeds to present a taxonomy for recommender applications, which classifies systems according to six characteristics:

(1) the method used to generate recommendations

(2) the inputs provided by the targeted customer

(3) the inputs provided by the customer community

(4) the outputs of the recommendation process to the customers

(5) the method of recommendation delivery

(6) the degree of personalization

Park (2012) identifies eight areas of application for customer recommender system research. In order of number of publications, they are: other (59; e.g., hotel, travel, and food), movies (53), shopping (42; online, offline, and mobile), documents (18; papers, blogs, and webpages), books (13), TV programs (9), music (9), and images (7). Although their search was largely confined to computer science and information systems journals, the number of categories is not likely to have differed if marketing journals were to be included in the search – many of the scenarios that have been investigated in marketing recommender systems research also fall into these categories. However, one issue here is that there is some overlap between these eight categories: all the categories can involve shopping. Therefore, their classification is not one that is necessarily useful for understanding the true scope of where recommender systems may be applied and delineating their application domains. Rather than application domains, the eight categories more specifically represent a few different types of products and services that may be suggested to consumers by recommender systems. These suggestions could occur on both retail and media platforms as sponsored and non-sponsored recommendations (Malthouse et al. 2019).

Undoubtedly, the market landscape in 2020 is different than it was in 2010. By 2030, the cutting-edge technology of today may hold no value at all; in fact, it may no longer even exist. Four of the six exemplars of e-commerce sites using recommender systems given by Shafer et al. (2001) are now defunct and no longer accessible. Technology drives consumer behavior and consumer culture, and thus, in part drives what the market values. Computer technology from just 10 years ago is considered practically ancient today and is valued little by the average American consumer. Many consumers simply through away their old and unused electronics, which is becoming an issue of global concern – 50 million tons of e-waste was generated in globally 2018 (Semuels 2019). Of course, that is not always the case; older technologies can have artistic or sentimental value or can even provide some specific utilitarian benefit that the latest technologies do not. For example, the latest video game console, or computer operating system, does not support games or applications developed for previous hardware generations. Other examples of "obsolete" but nostalgic technologies include vinyl music discs (record albums and the record players-turntables), film cameras (even Polaroid cameras), and old American muscle cars.

The point is that the basis for delineating application domains for recommender systems should not be specific products and services; fact is that the form, delivery, and consumption of today's products will differ with tomorrow's technology. A more appropriate basis for delineating the application domains of recommender systems would be the social domains in which shopping and consumption occur, or perhaps the ends for which, they occur. “To understand if and how a recommender system can be developed for a particular domain, one should first analyze the domain characteristics. Three characteristics are considered essential to understand a domain, (1) the actors and their roles in a system, (2) the type of data available to the recommender system that can be used to generate item suggestions, and (3) the demographics of user preference in a system community” (van Capelleveen et al. 2019). The survey of real-world recommender system applications by Lu et al. (2015) categorizes recommender systems with a similar perspective in mind and presents a potentially more enduring and meaningful classification.

Lu et al. (2015) cluster real-world recommendation applications into eight categories: (1) e-government, (2) e-business, (3) e-commerce/e-shopping, (4) e-library, (5) e-learning, (6) e-tourism, (7) e-resource services, and (8) e-group activities. In addition, they examine these applications through four dimensions: (1) recommendation methods (such as collaborative filtering), (2) recommender systems software (such as BizSeeker — a recommendation system for personalized government-to-business e-services), (3) real-world application domains (such as e-business), and (4) application platforms (such as mobile platforms). These areas identified represent the domains in which shopping and consumption occur. The recognition of such domains is essential for the development of accurate marketing knowledge as they represent the different intentions, motivations, and goal states that consumers have when shopping and consuming. A consumer performing the same behaviors in two different domains could have two different meanings. Simple pieces of data could not demonstrate these meanings; they can only be established by understanding the significance of the domain to the consumer.

RECOMMENDER APPLICATION DOMAINS

Lu et al. (2015) begin by reviewing the application of recommender systems in e-government contexts, which falls into one of two categories: government to consumer/citizen (G2C) and government to business (G2B). E-government "refers to the use of the internet and other information and communications technologies to support governments in providing improved information and services to its citizens and businesses." The application of recommender systems in this area is important as the number and complexity of government services available has increased. Citizens and businesses require assistance in becoming aware of and understanding the services available to them.

G2C recommender systems could be used by public administration offices at the state and federal levels to recommend services citizens are not currently taking advantage of (De Meo, Quattrone, and Ursino 2008). They could also be used as a part of the criminal justice decision to help judges' make jail or bail decisions based on the predictions of what a defendant would do if released (Kleinberg et al. 2018). Feedback to such systems could inform policy makers on developing more efficient and beneficial laws, policies, and government services, such as healthcare and financial aid. G2C recommender systems could conceivably even provide voting suggestions to citizens, although one would have to question the ethics and security of this type of application. Although, it could be argued that such systems have already been implemented, albeit unintentionally, via social media. Political content recommendations and targeted messages through social media have become a recent topic of controversy, allegedly being used to influence government elections around the world (Ali et al. 2019; Heater 2020; Salmon 2019; Schwartz 2018). A former Google engineer has argued that these kinds of recommendations are creating polarity and division in the U.S. population by driving users to adopt extreme viewpoints (Maack 2019). Recommender systems that prioritize maximizing content consumption often push extreme or controversial content to more users as this type of content gets higher engagement (more view time, comments, and shares). However, one recent study analyzing social media users would suggest that this issue may be overblown; a study of 50,000 consumers of online news found that social networks and search engines were associated with only a modestly increased mean ideological distance between individuals (Flaxman, Goel, and Rao 2016). Moreover, those same channels were also found to increase individuals' exposure to material from their less preferred political ideologies. Building recommenders with serendipity as a design principle has been suggested as a means to increase the diversity of information user's encounter as well as users' control over the information they receive. "As such the pursuit for serendipity can help burst filter bubbles and weaken echo chambers in social media" (Reviglio 2019, p. 151). Perhaps Facebook is justified in refusing to ban targeted political advertising (Ortutay and Anderson 2020). Facebook has also pledged to actively try to reduce the amount of time users spend on the platform; Zuckerberg wants users' time spent on Facebook to be more meaningful even if that means users spend less time on the platform overall (Kulwin 2018).

G2B recommender systems could be used by state and federal agencies to target services towards businesses that need them most. Such a system would be especially helpful during a national pandemic, for example, in which the government passed a bill to make trillions of dollars of aid available to businesses during the crisis. G2B recommender systems could also be used to raise awareness of government sponsored events and trade shows that businesses could benefit from or help them find partnerships or suggest government (public sector) contracts that would interest them. A G2B recommender system could also work the other way around by recommending private sector partnerships to government agencies. There are many ethical issues involved here and such systems may raise questions about if we are still operating in a "free" market. Some legal scholars comment on the potential legal ramifications of these systems and whether they may reduce freedom in a society (Stucke and Ezrachi 2017).

Another interesting use case is the application of recommender systems as aids to decision makers in the U.S. Department of Defense and Intelligence Community. Researchers from Lincoln Laboratory explore the development of such an application in depth and argue that these systems could help provide the computational support these agencies need to be less reactive and more predictive; for example, analysts could predict and respond faster to a cyber-attack (Gadepally et al. 2016).

Next, Lu et al. (2015) reviews e-business recommender applications. They distinguish e-business from e-commerce applications as those that are business to business (B2B) rather than business to consumer (B2C). They cite several examples of recommender systems that have been developed to assist in online auctioning, establishing trade relationships, banking and investment, and customer relationship management in the telecom industry. Following this they review e-commerce recommender applications that support the B2C online shopping experience, many examples of which are provided in chapter 1.

One area that has not often been studied in the B2C domain is hospitals and healthcare providers, although depending on the hospital, this type of system could fall into the G2C or B2C category. Cheung et al. (2019) and Stark et al. (2019) review the state of the art in medicine and healthcare recommender systems. These systems would help healthcare professionals quickly find suitable treatments based on the latest research, the current patient's profile, and similar patients' outcomes. However, consumers' receptivity to AI healthcare is another matter that needs to be consumers. Recent experiment research shows that consumers are reluctant to utilize healthcare provided by AI in both real and hypothetical choices (Longoni, Bonezzi, and Morewedge 2019). But perhaps this reluctance is mitigated when the healthcare comes from a provider who is using the AI/recommender system to aid his decision making, not to replace it. Burton, Stein, and Jensen (2019), who review algorithm aversion in augmented decision making, posits that keeping a human-in-the-loop of the decision-making process (by providing either real or perceived decision control to the user) enhances the decision maker's trust in the algorithm. In this case then, the increased confidence of the healthcare provider should theoretically also affect the patient's attitude towards the algorithm's advice. On the other hand, other studies show that lay people, as opposed to experts, are more likely to adhere to advice when they think it comes from an algorithm than from a person (algorithm appreciation as opposed to algorithm aversion) (Logg, Minson, and Moore 2019).

Digital libraries are another area of application identified by Lu et al. (2015). Recommenders in this domain can quickly help users select and locate knowledge and information sources thereby accelerating the development of new knowledge and information. They cite the example of an initiative of the Stanford University Digital Library Project which included the development of a system to provide recommendations on users' personal preferences. This system combined both CB and CF methods. Another example is the Internet Archive (www.archive.org), which is a non-profit organization dedicated to books, recordings, websites, and other cultural artifacts in digital form. Currently the website has digitized and archived over 20 million books many of which are no longer in copyright or print. The page for each item can make suggestions to similar texts based on the item's meta-data rather than the user's profile.

A very similar and perhaps not completely distinct application domain identified by Lu et al. (2015) is e-resource service recommender systems. These systems help users find resources that have been uploaded to the system by other users, which could include TV programs, webpages, documents, videos, and movie recommendations. The example of Mendeley, given in Chapter 1, could be argued to belong to either an e-library or an e-resource type system. Systems belonging to these two types could also be modified to make group recommendations. E-group activity recommender systems could be used to recommend books, movies, music, TV programs, and even travel destinations to a group of users who wish to consume together. Some examples of e-group systems are further discussed by Lu et al. (2015), though these types of systems could be used in both business and education settings.

An area of application closely related to e-library and e-resource is e-learning. Systems in this area could assist learners in choosing courses, subjects, materials, and learning activities that interest them and help them meet their educational goals. The system could provide a variety of information alongside its recommendations to help learners make choices, such as course difficulty, course format, and teacher rating. Information fed into these systems by learners could then be used by administrators and educators to adjust their course offerings and pedagogical approaches. These systems could also assist educators in advising students. As more institutions transition to online course offerings, the need for meaningful research in this area continues to grow, particularly as to how or if this type of system should be used to change the actual course content (e.g., two students in the same course receiving different levels of instruction from the system based on their performance).

Tarus, Niu, and Mustafa (2018) review 36 articles e-learning recommender systems that perform some of the aforementioned functions. Drachsler et al. (2015) also review e-learning recommender systems (a total of 82 articles spanning 15 years) and classify them into seven clusters them in terms of their contribution to the field:

(1) Recommending resources for learning based on CF

(2) Improving CF algorithms with e-learning in mind

(3) Using education constraints as sources of information

(4) Exploring non-CF methods to find successful educational recommendations

(5) Considering contextual information

(6) Assessing the educational impact of recommendations

(7) Recommending courses

An example of an e-recommender system is Google's Primer app (https://www.yourprimer.com/), which provides free personalized business education to users via their mobile device on topics such as branding and digital marketing. Rather than allowing users to directly select lessons from a catalogue, the app asks users what areas of business they are interested in and then offers personalized lesson suggestions. Users are not able to freely browse all lessons available in the app but must take suggested lessons or use the search function to explicitly search for a lesson. However, the full list of lessons is available to see online (https://www.yourprimer.com/en/lesson-catalog/2).

Perhaps the area of greatest potential is in using e-learning recommender systems to first assess users' knowledge of a topic (build the profile) and then provide them with a routine of simple practice exercises to bring them to the level needed for upcoming lessons from a human instructor. The lessons themselves could then be about discussing or creatively applying the knowledge they gained through the practice. In this way, educators would have to spend less time on teaching definitions and could spend more time on projects for students. More on e-learning recommender systems will be discussed in the future research section.

RECOMMENDATION GENERATION TECHNIQUES

Lu2015 review two types of articles in their survey recommender systems applications: (1) articles on recommendation techniques and (2) articles on recommender system applications. In total they review 177 articles. From the former type of article, they identify seven recommendation techniques (methods for generating recommendations): (1) content-based recommendation techniques, (2) collaborative filtering-based recommendation techniques, (3) knowledge-based recommendation techniques, (4) computational intelligence-based recommendation techniques, (5) social network-based recommendation techniques, (6) context aware-based recommendation techniques, and (7) group recommendation techniques.

However, what delineates these techniques is not completely clear as there is some overlap between them. There are only two types of recommenders (Yuan 2018): content-based and collaborative filtering-based. These two types can be combined or supported by a number of different computational and analytical approaches, some of which are mentioned in Lu et al. (2015). Lu et al. (2015) categorize content and collaborative filtering as distinct from other techniques. But that is not necessarily true as those other methods represent areas of application, specific pieces of information, or specific statistical approaches that are used to support the content or collaborative filtering approach.

What distinguishes recommender systems are the types of data they use. Three general types of data used by recommender systems are item data, user data, and user-item interaction data. Any specific piece of information can be classified according to these three types. For example, Lu et al. (2015) discuss what is referred to as context awareness-based recommendation techniques that use contextual information such as the time of year or social settings of the user. In their review, this technique and others are regarded as distinct from content and collaborative filtering systems. However, the use of contextual information does not necessarily warrant an additional category of recommender system. Information about the setting in which the user would purchase, consume, or otherwise interact with the product or service could belong to any of the three aforementioned data types. For example, AirBnB may suggest trips based on time of year. In this example, time of year could be item data (when the user would travel to the vacation destination) or user data (when the user is shopping for a trip). Thus, a system using contextual information could be either a content or collaborative filtering type of recommender system. There is no need for additional recommender systems classifications based on the type of data they use; all recommender systems can fall into the two aforementioned categories or combine them. Unnecessary classifications, categorizations, and labels can create contradictions and confusion. Sometimes it may even be best to leave things undefined.

However, recognizing and organizing the current computational and analytical methods (techniques) for generating recommendations would provide much value and help better organize the recommender systems research. In this respect, the categorization of techniques by Lu et al. (2015) is a valuable contribution. They highlight several methodologies that could conceivably be applied to either content or collaborative filtering type recommender systems. Similarly, van Capelleveen et al. (2019) broadly conceive of recommender techniques as various classes of filtering algorithms: (1) collaborative filtering, (2) content-based filtering, (3) demographic filtering and context-based filtering, (4) knowledge-based filtering, and (5) hybrid filtering. The review by Park et al. (2012) also provides value by identifying eight data mining techniques used by recommender systems: (1) association rule mining, (2) clustering, (3) decision tree, (4) k-nearest neighbor, (5) neural network, (6) link analysis, (7) regression, and (8) other heuristic methods. The methods identified by Lu et al. (2015) could be placed into these eight categories. Alternatively, Portugal2018 classify data mining (machine learning algorithms) more specifically into 15 categories: (1) Bayesian, (2) decision tree, (3) matrix factorization-based, (4) neighbor-based, (5) neural network, (6) rule learning, (7) ensemble, (8) gradient descent-based, (9) kernel methods, (10) clustering, (11) associative classification, (12) bandit, (13) lazy learning, (14) regularization methods, and (15) topic independent scoring algorithm.

2.1.2 Designing to Support Choice-Making Patterns

As demonstrated, recommender systems are tools that can help people make better choices, both small and large, in a variety of domains. In a chapter reviewing recommender systems and human decision making, Jameson et al. (2015) view recommender systems with the perspective that they are tools for helping people make small everyday choices, such as what products to buy, documents to read, etc, rather than tools for helping with large complex decisions, such as how the Department of Defense should respond to a cyber-attack. Considering that people's decision-making processes change when the stakes are higher (Kahn and Baron 1995; Kunreuther et al. 2002), distinguishing between small to medium size choices and large complex decisions makes a lot of sense. Jameson et al. (2015) also argue that it best to keep a person in the decision-making loop and that when a system makes the choice for the user, such as automatically choosing songs for a listener, then it is no longer a recommender system but "an agent that performs tasks on behalf of a person." In essence, the *recommender* system becomes a *decision* system. In their view, the purpose of a recommender system is to help make people the choices that would be most satisfied, which would sometimes mean allowing the user to reject a recommendation or making no choice at all, something which an autonomous decision system would not be able to do. Considering these two perspectives (the control someone has in their decision making and the complexity of the decision needing to be made) seem to be very relevant considerations for the design of any system aimed at helping users make satisfying choices.

To help understand how recommender systems could assist users in making more satisfying choices, Jameson et al. (2015) review the psychology of everyday choice-making , which ideally keeps the chooser in the loop in one of two basic ways: (1) the system only takes over a part of the processing that is required to make a choice and leaves the rest up to the user (e.g., presenting a small subset of options based on from a large database based on filters specified by the user), and (2) the system generates an overall recommendation, but also presents an explanation of how the recommendation was generated (i.e., why the item was recommended). Jamesom et al. (2015) review people's choice making processes using the ASPECT model (Attributes, Social Influence, Policies, Experience, Consequences, and Trial and Error). Then, they review strategies for helping people make better choices using the ARCADE model (Accessing user information and experience, Representing the choice situation to the user, Combining and computing, Advising users about processing, Designing the domain, Evaluating on behalf of the user). The ARCADE model can be used to design recommender systems that support people's natural choice making processes described by the ASPECT model. Such systems should theoretically help users attain the highest possible satisfaction.

Table 2-1: Examples of the six facets of the ASPECT model for customer choice-making strategies and ARCADE model for choice-supporting recommender design.

ASPECT	**ARCADE**
Attribute-based choice	**A**ccessing information
"Does this product have the attributes I desire?"	Providing information on other users' experiences
Socially-based choice	**R**epresenting the situation
"What choice did others make?"	Presenting one recommendation at a time
Policy-based choice	**C**ombining and computing
"I will always buy this brand of product."	Allowing users to filter or cluster items
Experience-based choice	**A**dvising about processing
"Have I had a good experience with this brand before?"	"We suggest you consider these attributes when choosing."
Consequence-based choice	**D**esigning the domain
"What will happen to me in the future as a result of this choice?"	"What options should we make available in our system?"
Trail-and-error based choice	**E**valuating for the chooser
"I wonder what this candy tastes like."	"Based on your responses we suggest…"

The ASPECT Model

The ASPECT model distinguishes six human choice patterns, which are sometimes used in isolation or together:

(1) **A**ttribute-based choice

(2) **S**ocially-based choice

(3) **P**olicy-based choice

(4) **E**xperience-based choice

(5) **C**onsequence-based choice

(6) **T**rial-and-error-based choice

With each choice pattern, researchers and designers of recommender systems can ask "What steps are involved in each choice pattern and what can a recommender system do to help people execute these steps more successfully?" Jameson et al. (2015) argue that recommender systems should ideally help people execute these steps more successfully rather than completely take over the choice process.

Attribute-based choice involves the chooser sees items in terms of attributes (e.g., price and performance) and levels of attributes. The attributes are evaluated by the chooser to assess the desirability of an item. This choice process involves four steps: (1) identifying the attributes desired, (2) identifying the desired level and importance of the attributes, (3) identifying items with those attribute levels, and (4) choosing an item from the consideration set. A recommender system can help in all these steps if it is able to acquire some information (hypotheses) about the user's desired attribute levels. It could even recommend desired attributes if the user is unfamiliar with the product category by asking them simple questions, for example.

Socially-based choice involves the chooser considering the examples, expectations, and/or advice of others when making a choice. Collaborative filtering systems could be argued as supporting this choice process as they consider the similarity between groups of users when generating recommendations. However, there are some ways the system could involve the user in the decision process and more explicitly help them make a socially-based choice. For example, the system could recommend experts whose advice the chooser can then take into account, or the system could recommend behavioral norms that would help a user become a well-regarded member of a social group.

Policy-based choices making involves the chooser first arriving at a policy, either by considering past-experiences or anticipating a potential upcoming situation, then applying that policy when faced with a choice to make. Related concepts to this choice process include choice bracketing and self-control. Recommender systems could support a policy-based choice making process by recommending possible policies to follow, for example, a diet or exercise routine, which would involve the user making choices that adhere to the routine. The system could also help users apply policies; for example, a user can set up their preferences in Apple News to be shown on certain types of news stories.

In the consequence-based choice process, the chooser contemplates what the outcome of their choice will be. For example, a student might choose a course based on how useful they believe it would be for landing a desired job. The chooser needs to consider the uncertainty about what the long-term consequences of their choice will be. To help alleviate this uncertainty, a recommender system can help users recognize when the stakes for making a choice are higher or bring awareness to options that they did not know about. The system could also present warnings to the user about the possible outcomes of their choice.

In contrast to attribute-based and consequence-based choice, the four remaining ASPECT patterns involve processes that are typically quicker and less effortful on the part of the chooser. Experience-based choice occurs when the chooser incorporates past experiences with the choices or situation into their decision-making process. For example, a consumer may feel hesitant to choose a game from a developer that has often released buggy or incomplete games. In this process, the chooser analyzes relevant past experiences and would tend towards the choices they had experiences with in the past. One way that recommenders could support this process is by remind the user their past choices and their feelings as a result of them, an approach which has been referred to as *recomindations*, or, augmented memories (Plate et al. 2006). For example, a system could remind a user how they review/rated similar games in the past.

When none of the other choice patterns are clearly applicable, a chooser may apply a trial and error process; chooser's simply pick an option, even at random, to see how well it works out. By the knowledge gained through trial and error, the chooser can make more accurate and satisfying decisions in the future. There are a couple of ways in which recommender systems can support this choice process. One is by providing users with a series of options so they can try out a variety of items to learn what they like. Another is by incorporating users' experience with trailed items to identify what attributes are important to them so that subsequent recommendations will maximize those attributes.

The six choice patterns are often used in combination, and therefore, recommender systems can also combine these patterns to support good choice making. But what constitutes a “good choice?” Jameson et al. (2015) suggest that a good choice is made when people feel good about their choice (are satisfied). Based on previous research they identify four generalizations that help explain when people feel that they have chosen well: (1) Choosers want their decisions to yield good outcomes, (2) Choosers don’t want to invest time and effort in the choice process itself that is out of proportion to the resulting benefit, (3) Choosers tend to prefer to avoid unpleasant thoughts, and (4) Choosers often want to be able to justify the decision that they have made to other persons or to themselves.

<u>The ARCADE Model</u>

ARCADE is a model of six choice supporting strategies that can be implemented within recommender systems:

(1) **A**ccessing user information and experience

(2) **R**epresenting the choice situation to the user

(3) **C**ombining and computing

(4) **A**dvising users about processing

(5) **D**esigning the domain

(6) **E**valuating on behalf of users

The first is by accessing information and experience. This is the most obvious way of helping choosers. The system can provide relevant information to help choosers understand what kind of experience their choice will get them. This can support a consequence-based pattern by giving preview of films, for example, or support a socially-based pattern by informing the user about what similar users chose. Functions performed by the system could include information retrieval, life logging, providing multimedia to users, integrating social media, and integrating simulations and games.

The second strategy in the ARCADE model is representing the choice situation. This specifies how the recommendations will be organized and displayed to the user. For example, recommendations could be presented one at a time or simultaneously, or, as another example, the user could evaluate an entire category or brand rather than items individually. The way information is organized and represented to the user has consequences for the chooser's processing pattern, which potentially affects the satisfaction with his choice. The primary function performed by the system to execute this strategy would be information visualization.

The third strategy is to combine and compute. Recommenders can provide options for choosers to specify simple and sophisticated computations for the system to perform. Some examples of simple computations would be sorting or filtering items based on some attribute. More sophisticated computations consist of clustering items based on identified user preferences regarding attributes or even automatically based on inter-item similarity. Functions needed to execute this strategy could include sorting and filtering, diagnosis and prediction, clustering, and machine learning (Pantano et al. 2019).

The fourth strategy involves advising the chooser about the processing. This involves communicating to the user why the recommendation was made. The reason given can be simple such as "other customers also viewed…" but it could also be more personalized to the chooser by incorporating past experiences or even social expectations. For example, Google Assistant telling a user who asked for running shoes recommendations: “I see that in the past you purchased blue running shoes. Here are the latest designs in blue.” Conversational agents, chatbots, and hyper personalization would be a primary function of a system applying this strategy (Thomaz et al. 2020).

The fifth strategy is to design the domain. In this strategy the recommender system crafts the options and other aspects of the choice situation, as well as how the choice is presented to the chooser, to make it easier for the chooser to make the right choice. Jameson et al. (2015) give the example of a recommender system helping a user choose the most appropriate privacy settings on a social media site. One strategy (representing the choice situation) would involve grouping related options together. But if the privacy settings are complex and interdependent, then it can make it difficult to apply the representing the choice strategy. Under the designing the domain strategy, the designer would first need to reconceptualize the privacy options and underlying privacy management principles themselves so as to make the choice situation easier for the chooser and recommender system. Apple’s design of privacy settings on the iPhone takes such an approach. For example, under the iPhone’s Analytics & Improvements settings, users are given only a handful of options to control their privacy settings when really each of these options enables or disables the sending of numerous pieces of information to Apple.

Lastly, the sixth strategy is simply to evaluate on behalf of the chooser and advise them on the next step to take in the choice process. The evaluation could be made involving the preferences of the chooser (“Because you liked that we recommend this”) or simply based on the context of the application (“It is recommended to close all programs before installing this software”). The six strategies of the ARCADE model can be combined to support the choice making patterns described by the ASPECT model.

2.1.3 Designing to Bias Choice

Jameson et al. (2015) review the potentially destroying influences that recommenders can have on the choice-making process. Typically, a recommender system will reduce a large item set to a smaller set that the user can choose from. However, how this selection process takes place influences the distribution of items that get selected by individuals. In addition, the way the options are visually represented and what information is presented alongside each option influences what choosers select. Understanding how the selection and representation of items influence choice is of interest to system designers and researchers who are investigating consumer choice making. A system can have unobvious drawbacks and/or benefits for the chooser, which, if left undiscovered, can lead to misunderstandings about the system’s effectiveness and why consumers made the choices they did. There are five ways a system can bias consumer choice:

(1) Context effects

(2) Order effects

(3) Framing effects

(4) Priming Effects

(5) Defaults

Context effects occur based on how one choice looks in comparison to the other choices. In recommender systems, this typically occurs as a decoy effect. For example, let’s say there are three items in a choice set: A, B, and C. Option A is better on some attributes while option B is better on other attributes. Option C is worse than A on all attributes and is there to make A look more attractive as an option. This can bias customer choices towards option A. Another example of a context effect is the compromise effect where an option tends to be viewed relatively favorably if it can be seen as a compromise (for example, on price vs. feature set) compared to the other options in the item set.

Order effects occur primarily as a result of the way consumers process information. When presented with several options, consumers will examine them selectively, typically in the order consumer encounters the options and information. Here choosers may adopt a choice strategy that satisfices, meaning that they will stop examining options once they find one that is "good enough" even when they know that a better option may be found with additional effort. Even when all options have been examined the final choice may be influenced by primacy and recency effects (favoring the first or most recent options viewed).

Framing effects occur based on how a choice situation is represented and can manifest in three ways: (1) attribute framing, (2) risky choice framing, and (3) goal framing. Attribute framing is most relevant to e-commerce settings as the attributes of a recommended option can be formulated as positive or negative (e.g., 75% lean vs 25% fat). Jameson2015 propose that designing the recommender system to present all options with the same type of framing can help mitigate this biasing effect. Similarly, by framing the outcomes of all choices in the same ways, the effects of risky choice framing and goal framing can be mitigated.

Priming effects occur when exposure to a stimulus increases the accessibility of information in the subject's memory that is related to that stimulus. Priming effects can influence choosers to weigh certain attributes (e.g, price, durability, etc.) over others, even if they have considerable experience in the product domain. To use this effect to help customers, recommender systems can adaptively incorporate primes for the attributes that have been identified as most important for the customer. Doing so can push choosers to pay more attention to the attributes that matter the most, which should lead to more satisfying choices.

Lastly, choosers may be biased towards choosing a default option. There a few reasons why: (1) the chooser is not aware of additional options, (2) the chooser may assume that the default is the most recommended and thus the best option, or (3) the chooser does not desire to expend the physical or mental effort required to consider the other options (e.g., there are less clicks and input needed to make a choice). Recommender systems can set the default option dynamically depending on what it computes to be the ideal option for the user; however, a system designed with the goal of maximizing the autonomy of the decision maker (i.e., the chooser should explicitly state/approve of all inputs) should perhaps minimize the use of defaults.

Researchers have begun to uncover that not only can recommendations bias choice and economic behavior (Adomavicius et al. 2018), but they can bias post-consumption evaluations and preference ratings, which could negative impact the quality of information used to generate recommendations (Adomavicius et al. 2013, 2014; Adomavicius, J. Bockstedt, et al. 2019). For example, one study found that "if the recommendation that is observed before item consumption is perturbed by 1 star (on the 1 to 5 star scale), the user's self-reported post consumption preference rating is shifted, on average, by 0.35 in the direction of biased recommendation" (Adomavicius et al. 2019, pp. 1324-1325, referring to Adomavicius et al. 2013). Two general strategies that have been suggesting for de-biasing a person: modifying the person or modifying the environment (Keren, Wu, and Soll 2015). Adomavicius et al. (2019) argue for the latter approach, which involves how information, such as ratings, is presented to the user. They test how various rating display formats can be used to debias user's and find that it is unlikely for post-consumption biasing effects of ratings to be completely eliminated.

Understanding how recommenders affect choice evaluations and biases as a variety of aspects of the user choice experience can be affected by biases: perceptual category breadth, the use of functional and nonfunctional product dimensions, decision time, and choice confidence (Park and Lessig 1981).

2.1.4 Evaluating Goals and Performance

Inspired by the ontological business model canvas theory, van Capelleveen et al. (2019) develop a model for developing and documenting recommender system design. Their model helps designers understand what key decisions they need to make to align the value provided by the system with company objectives. To develop this model they review six areas of research:

(1) The goals of recommender systems: *what do we try to achieve with the recommender?*

(2) The domain characteristics in which recommendation takes place: *what characteristics may influence the design?*

(3) The functional design considerations of recommender systems: *what functionality does the user expect in the design?*

(4) The filtering techniques for creating recommendations and the techniques for soliciting data to create a sustainable basis for recommender system to recommend upon: *what techniques best apply to this case?*

(5) The interface of a recommender systems: *how to present the recommendations?*

(6) The evaluation and optimization mechanisms for a recommender system: *how to test the recommendations and make sure that they remain relevant to users?*

These areas are further broken down into 22 subsections that comprise the recommender canvas model. The purpose of the canvas is to help share and develop a common understanding about recommender design concepts so as to help the business design systems that align user goals with organizational goals. With its goals defined an organization can then identify the metrics that will help them evaluate how well the system is helping users and the organization achieve those goals. “Most prevalent goals relate to accuracy, coverage, confidence, trust, novelty, serendipity, diversity, utility, risk, robustness, privacy, adaptability, scalability, and behavioral change” (van Capelleveen et al. 2019).

Evaluating how well a system has achieved its goals (how well it is performing) can involve measuring changes to the company bottom line, changes in the perceptions and behaviors of users, and changes in key statistics relating to item data and recommendation algorithms. The performance of a system are significantly influenced not only by the selection of algorithm but also other functional and interface design considerations (van Capelleveen et al. 2019).

Table 2-2: Examples of the functional and interface design characteristics of recommenders systems that should be considered for aligning consumer and business goals to achieve optimal performace (van Capelleveen et al. 2019).

Functional Considerations	**Interface Considerations**
Personalization	Presentation Modality
Recommending based on user's highly rated brands	Will communicating the recommendation involve text, speech, or graphical displays?
User Control	Item Organization
Allowing users to change their preference profile	Will recommendations be grouped based on reason for recommendation?
Interactivity	Item Notification Context
"Show me more like this."	Will recommendations given by push or pull?
Context Awareness	Item Information
Taking into account users' time, location, activity, etc.	What item attributes will be communicated in the recommendation?
Restrictions	Item Explanation
Designing around privacy	"Customers like you liked…"

Functional design considerations for recommender systems consist of five elements:

(1) Personalization

(2) User control

(3) Interactivity

(4) Context Awareness

(5) Restrictions

These considerations represent the functional relationship between the user and the recommender algorithm. The degree of personalization has several facets: both the content and the interface can be personalized for individuals or groups and use a variety of data. “Personalization can be defined as the ability to proactively tailor products and product purchasing experiences to tastes of individual consumers based upon their personal and preference information” (Chellappa and Sin 2005). User control refers to users’ ability to influence the operation of the recommender system. Experiments suggest that users provided with more control respond more positively to recommendations, even when they found the interface more cumbersome (Harper et al. 2015). More control can be provided by letting users select the recommendation algorithm to be users, adjust the parameter settings of those algorithms, and make changes to their user data that is used by the algorithm. Interactivity allows a system to more accurately model users preferences be soliciting explicit feedback from on recommendations (e.g., “Show me more like this”). Interactivity allows the user to take a conversational approach with the recommender system, which would benefit users facing complex decision making problems and thus be more likely to invest additional effort in the process. Context awareness in a recommender system can be facilitated through a variety of means: (1) time awareness, (2) location awareness, (3) activity awareness, (4) device awareness, (5) body awareness, and (6) social awareness. Context awareness can help a system recommend the right item at the right time and place. Lastly, design restrictions must be considered as part of the functional design characteristics, which may impair the effectiveness of the system. Restrictions can refer to measures taken to protect user and stakeholder privacy and security as well as the architectural complexities of the system.

Interface design for recommender systems is about deciding how, when, what, and where to present an item. There are five dimensions to recommender system interface design:

(1) Presentation Modality
(2) Item Organization
(3) Item Notification Context
(4) Item Information
(5) Item Explanation

Recommendations can be presented in several ways: auditory, nonverbal gestures, and visual. Visual presentation of recommendations is the most common. The composition of the visual design influences how users experience and act upon recommendations" (van Capelleveen et al. 2019, p. 22). The design choices may affect users' opinions of the items themselves (Adomavicius et al. 2019) and how much they trust the recommendation and find it useful (Ghasemaghaei, Hassanein, and Benbasat 2019; Lui and Hui 2010; Panniello, Gorgoglione, and Tuzhilin 2016; Wang and Benbasat 2005). Visual presentation can consist of text, icons, and images that communicate information about the item, what other users thought of the item, how the item is related to other items, why the item is being recommended (item explanations), and what actions the user can take, which all ultimately influence what item gets chosen. Item information and item explanation can also be considered as part of the visual presentation. Display order is another aspect of visual presentation that can affect what items users choose through position, faming, and decoy effects, for example (Teppan and Zanker 2015). Display order also belongs to the item organization dimension. In addition to the order recommendations are displayed, item organization decisions involve considering how those items will be ranked, how the rankings will be presented to the user, how many items will be displayed, and what options the user has to reorganize the items or compare them.

Interface design choices related to the notification/recommendations context involve considering the time and place users can receive notifications/recommendations. The information in the notification, or whether or not users are to receive notifications at all, can depend on the time of day, location, social setting, and activities a user is engaged in. In addition notifications can be pushed to users automatically (push) or only provided upon user request (pull). Wang and Zhang (2013) develop a new model for identifying the ideal time to make recommendations and examine this model in push and pull scenarios. They found the performance of their model differed in each scenario: data on repurchase behavior collected by a real-world e-commerce website show the model "significantly improves the conversion rate in pull-based systems and the user satisfaction/utility in push-based systems" (Wang and Zhang 2013, p. 303).

All the aforementioned aspects of functional and interface design affect the performance of a system. Adjusting any one of the design choices can affect any number of metrics a company may be measuring. The performance metrics of interest depend the goals the company has set out for the system. Metrics could be based on user behavior (e.g., click-through rates, conversion rates, time spent on the site, etc.), user evaluations (e.g., trust, satisfaction, usability, etc.), and key statistics related to ranking algorithms (e.g., precision and recall, Normalized Discounted Cumulative Gain, Mean Reciprocal Rank, and others (van Capelleveen et al. 2019; Yuan 2018)). The latter type of metric represents the accuracy and error of the recommender, which typically involves comparing an algorithm's prediction against a user's rating of an item.

McNee, Riedl, and Konstan (2006) argue that relying too much on accuracy metrics harm recommendations as maximizing accuracy means maximizing the similarity between items the user has previously consumed, which is not always what the user wants. For example, users may not find a travel recommender system that only recommends places similar to where they have been very satisfying. Moreover, recommender accuracy does not always lead to increased user satisfaction (Wu, Joung, and Lee 2013). Measuring serendipity and user centric metrics to evaluate performance help the development of more satisfying recommenders (McNee, Riedl, and Konstan 2006). Diversity and coverage are two measures also that could also be used to evaluate performance in terms of the enhancing the usefulness of the recommender to users (Jannach and Jugovac 2019; Yuan 2018).

Ultimately, the recommender systems needs to be meeting the goals of both business and the users, which means that the system needs to be creating value for all parities. Jannach and Jugovac (2019) review the literature pertaining to the challenges involved in measuring the business value of recommender systems. In general, the business value of recommendation and personalization is thought to be quite high. For example, Netflix estimates the business value of their recommendations at more than 1 billion US dollars per year as it helped decrease customer churn over the years. Adamopoulos and Tuzhilin (2015), who explore the business value of different types of mobile recommendations, find an increase of 10% in the number of recommendations raises demand by approximately 6.7%; other studies find recommendations to have much lower effects on demand (Lin, Goh, and Heng 2017; Zhao et al. 2018). Thus the true value can be difficult to asses as it can vary depending on the market and what metrics are evaluated. Moreover, the value of an algorithm may not translate equally to all domains and neither would all metrics be equally relevant. Some general approaches to measuring the value of a recommender include click-through rates, adoption and conversion, sales and revenue, effects on sales distributions, and user engagement and behavior (Jannach and Jugovac 2019).

2.2 Recommenders and Choice Difficulty

2.2.1 Choice Overload

Consumers are faced with a growing number of choices every day for many aspects of life: careers, education, places to live, places to travel, products to buy, and services to receive. Many researchers have investigated how the number of choices can affect the customer choice experience and some have found that too much choice can negatively affect choice satisfaction – an effect named “choice overload” or “the paradox of choice” or other similar terms (Scheibehenne, Greifeneder, and Todd 2010; Schwartz

2016). Like information overload, choice overload can make it difficult to know exactly which option to choose as the complexity involved in weighing preferences between options can increase. For example, if a chooser is using an attribute-based choice strategy, they will have to compare the attributes of more options and possibly have to make more cognitive effort. Although many researchers have identified significant negative effects from choice overload, a meta-analysis of 50 studies revealed mixed results (Scheibehenne, Greifeneder, and Todd 2010).

Scheibehenne, Greifeneder, and Todd (2010) conduct a meta-analysis of 63 effects from 50 experiments (N = 5036) seeking to explore to the adverse effects of choice overload and the conditions under which it occurs. They note that the negative consequences of having too much choice has been observed in studies on a variety of items, such as jams (Iyenger and Lepper 2000), chocolates (Chernev 2003a), gift boxes (Reutskaja and Hogarth 2009), pension plans (Sethi-Iyengar, Huberman, and Jiang 2004), and pens (Shah and Wolford 2007). These studies have observed that large assortment sizes (a large number alternatives to choose from) have negative effects on choice participation, satisfaction, and purchase behavior.

However, Scheibehenne, Greifeneder, and Todd (2010) also note that previous researchers have suggested that that are some preconditions that must be met for these negative effects to occur. One is a lack of familiarity with the items in the choice assortment (Iyenger and Lepper 2000): choosers are not be able to easily identify the item that is most preferred. However, people with clear preferences for a product category prefer to choose from larger assortments and experience higher satisfaction as a result (Chernev 2003a; b; Mogilner, Rudnick, and Iyengar 2008). Another consequence of unclear preferences is that there will be no obviously dominant option to choose from, which can also make the choice more difficult. A lack of familiarity, preferences, and no obvious option can lead to choice overload when choosing from large assortment sizes, but when exactly are the number of options too many? Most likely, choice overload occurs "in novel situations with an excessive number of options such that the assortment exceeds ecologically usual sizes" (Scheibehenne, Greifeneder, and Todd 2010, p. 441).

Another suggested condition for when choice overload can occur is that when the choice is made within a category, rather than across categories; choice becomes more difficult because all the items in the assortment are similar and an attractive option is not easily identifiable. Additionally, large assortments may induce fears of not being able to choose optimally, induce a lack of motivation to make the effort to compare all items, make it difficult to justify the option chosen, and regret about an option not chosen. The effort required to make a choice from a large enough number of alternatives may deter some people from making any choice at all (Kahn and Lehmann 1991). Together, the consequences can decrease the chooser's overall satisfaction.

On the other hand, large assortments can mean a larger variety of choices to increase the likelihood of satisfying more customers, giving retailers with larger assortments a competitive advantage (e.g., Walmart and Amazon). A large assortment available in one place can reduce searching costs for more options and potentially allow for easier comparisons between options, which can lead to better-informed, more confident decisions (Curtis and Lipsey 1979; Hutchinson 2005). Some researchers have found that sales decreased when fewer options were available for customers, which seems to indicate the opposite of the choice overload effect (Borle et al. 2005). In addition, increasing the number of options, even when all options are equally valued, has been shown to increase feelings of choice freedom and satisfaction (Reibstein, Youngblood, and Fromkin 1975).

Thus, Scheibehenne, Greifeneder, and Todd (2010) suggest the need for further investigation and conduct a meta-analysis to ascertain the robustness of the choice overload effect. The dependent variable was a composite of satisfaction with the chosen option, a dichotomous variable indicating whether an active choice was made, total amount consumed, and willingness to exchange a chosen option at a later point. Moderators included various characteristics of the studies such as the year the study was conducted and whether the dependent variable was satisfaction or choice. Although many individual experiments showed large assortments to have a positively affect outcomes, just about as many experiments showed negative effects. The overall mean effect size was found to be near zero (d = 0.02; CI_{95} = [-0.09, 0.12]); however, the variance between the studies was reported as medium to high ($Q(62) = 192$; $p < 0.001$; $I^2 = 68\%$).

Although Scheibehenne, Greifeneder, and Todd (2010) were not able to assess the moderating effects of assortment structures, choice-making strategies, perception of choice distribution, and satisfaction with other aspects of the choice experience, they go on to elaborate how these aspects of the choice experience could influence choice overload.

Related to assortment structure, they comment on (1) categorization and option arrangement, (2) difficulty of trade-offs, (3) information overload, and (4) time pressure. Arranging options into categories or a discernable structure may help mitigate the negative effect of choice overload on satisfaction (Mogilner, Rudnick, and Iyengar 2008).

Categories make it easier for the chooser to filter alternatives and decrease the cognitive effort needed to make the choice, especially in unfamiliar choice situations. However, most of the studies in the meta-analysis that did not observe the effects of choice overload also that did not arrange the options into categories. The difficulty of assessing trade-offs between alternatives can affect choice, satisfaction, regret, and motivation (Hoch, Bradlow, and Wansink 1999; Kahn and Lehmann 1991; Zhang and Fitzsimons 1999). This can occur because the options possess elementary or unique features that are not directly comparable or is the assortment size is large (Chernev 2005; Gourville and Soman 2005). Presenting too much information, especially complex information, can lead to choice overload (a special case of information overload) because it can make it difficult for the chooser to process the most relevant information. Considering additional information also uses more of the chooser's time and may affect motivation to compare all alternatives. Information overload is influenced by the number of item attributes and the distribution and levels of those attributes. (Greifeneder, Scheibehenne, and Kleber 2010) found that satisfaction decreases with large assortments only when the items were described on many attributes. Lastly, choosers can experience decreased satisfaction and regret from more options when they felt they were being rushed. Too little time may result in the chooser feeling overwhelmed with the options and information. In an unfamiliar choice situation, the chooser maybe unsure of what information to prioritize their time on processing.

Related to choice-making strategies and motivations, Scheibenne2010 comment on (1) relative versus absolute evaluations, (2) maximizing, (3) choice justification, and (4) simple choice heuristics. The degree to which choosers are considering the relative attractiveness of an option, which can increase with increasing assortment size and item similarity, when a chooser selects from an assortment then decides to make a purchase (rather than deciding to make a purchase from the assortment beforehand) has been observed to result in choice overload (Leilei and Simonson 2008). Also, the degree to which the chooser is willing to search for the relative best option, as opposed to simply the first satisfactory option identified, reflects the degree of maximizing (versus satisficing) in the chooser's strategy. Maximizers are sometimes less satisfied with their choice compared to satisficers (Dar-Nimrod et al. 2009) and although they generally prefer larger assortment sizes, they tend to find it more difficult to commit to a choice. Choice justification may result in choice overload when choosing from extensive sets as the larger number of options makes, especially if they are similar, can make it harder to justify the choice made (Scheibehenne, Greifeneder, and Todd 2009). Lastly whether choosers make use of simplifying choice heuristics could affect the degree to which the chooser experiences choice overload. Examples include satisficing, elimination-by-aspects that quickly removes unattractive options from the consideration set, choosing the default option, the consideration set-model that balances search costs and expected outcomes.

The aforementioned strategies are ultimately be influenced by the perception of the choice distribution. The variability in quality and characteristics of the options in a given assortment can influence choice overload. When the options in both a large and small assortment are assumed to be equal in terms of attractiveness and quality, customers are less likely to prefer the large assortment over the small one (Chernev 2005).

Lastly, Scheibehenne, Greifeneder, and Todd (2010) consider whether choice overload differentially affects satisfaction with different aspects of the choice experience: with the single chosen option, with the choice process, with the choice experience as a whole, and with future choice. For example, if a chooser engages in a trial-and-error choice strategy he may enjoy the choice process where he learns about the different options, even with a large assortment, but may not be satisfied with his final choice. This may be more likely to occur when making choices among exotic and hedonic products. However, Scheibehenne, Greifeneder, and Todd (2010) find that satisfaction with the choice process and perceived difficulty of the choice consistently change with assortment size; although, the analysis revealed no liner or curvilinear relationship between effect size and the number of options in the large set. On the other hand, too many options can lead to difficulties assessing the benefits of any one option and whether or not a better option exists. This situation can result in choosers deferring their choice until a future time, another manifestation of choice overload.

A larger and more recent meta-analysis on choice overload found more evidence concerning when choice overload occurs (Chernev, Böckenholt, and Goodman 2015). The meta-analysis consisted of 99 study-observations (N = 7202) and showed a significant overall effect of assortment size on choice overload (d = 0.41; SE = 0.14; t = 3.0; p = 0.01). Moreover, the study identified four key factors that moderate the effect of assortment size on choice overload: (1) choice set complexity, (2) decision task difficulty, (3) preference uncertainty, and (4) decision goal. The analysis showed that these four variables have a significant positive effect on choice overload, whether it is measured as satisfaction/confidence, regret, choice deferral, and switching likelihood. Lastly, when the four moderating variables were considered, the overall effect of assortment size on choice overload was found to be significant.

Chernev, Böckenholt, and Goodman (2015) argue that offering customers a large assortment can either help or hinder choice. On one hand, the more options a customer has the more likely they are to find something that matches their preferences or purchase goals and gives them the opportunity to discover more products. This will especially be the case when a customer can find everything that they need in one store (e.g., Walmart). But on the other hand, evaluating all the alternatives in a large assortment comes at the expense of increased time and effort, which can also reduce purchase rates. Additionally, large assortments have been found to shift consumers' expectations for what options they should expect. For example, a customer may believe expect that because the assortment is large that they should be able to find their preferred option or even something better. As a consequence, choices from a large assortment can lead to disconfirmation of the customers' expectations, resulting in a delayed choice and a lowered satisfaction with the choice (Diehl and Poynor 2010).

In describing choice overload, Chernev, Böckenholt, and Goodman (2015) go on to elaborate on its characteristics and consequences. First, how is choice overload measured? Choice overload is a mental construct that refers the state of a individual who faces a choice making problem that exceeds his cognitive resources. Two types of indicators are use to observe choice overload: "process-based indicators describing the subjective state of the decision maker and outcome-based indicators reflecting the decision maker's observable behavior" (Chernev, Böckenholt, and Goodman 2015).

Choice overload as a subjective state is typically captures by changes in consumers' choice confidence, satisfaction, and regret, whereby higher levels of choice overload are presumed to produce lower levels of these internal states. Changes in behavior that are thought to occur as a consequence of choice overload include (1) being less likely to make any choice at all, (2) being more likely to reverse initial choice (which may suggest low confidence in choice), (3) being less likely to display a preference for larger assortments, and (4) being more likely to choose an easily justifiable option.

The numerous studies included in the meta-analysis identify a variety of factors that may influence choice overload, which can make it difficult to generalize and explain the results between the studies (Chernev, Böckenholt, and Goodman 2015). However, these factors can be classified as belonging to one of two types: extrinsic (objective) factors and intrinsic (subjective) factors. Extrinsic factors are those that a relative to the choice problem, such as choice set complexity decision task difficulty, whereas intrinsic factors are those are relative to the chooser, such as preference uncertainty and decision goal. Furthermore, extrinsic factors can be conceptualized as task factors (decision task difficulty) and context factors (choice set complexity).

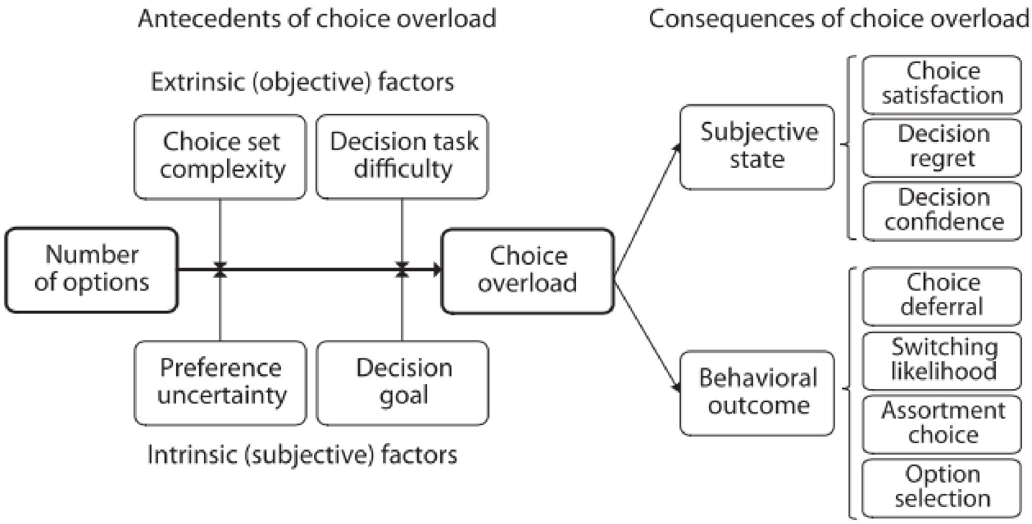

Figure 2-1: The model of assortment size on choice overload tested by Chernev, Böckenholt, and Goodman (2015).

The four moderating factors were operationalized as follows: "(1) The *complexity of the choice set* describes the aspects of the decision set associated with the particular values of the choice options: the present of a dominant option in the choice set, the overall attractiveness of the options in the choice set, and the relationship between individual options in the decision set (alignability and complementarity; (2) the *difficulty of the decision task* refers to the general structural characteristics of the decision problem: time constraints, decision accountability, and number of attributes describing each option; (3) *preference uncertainty* refers to the degree to which individuals have articulated preferences with respect to the decision at hand and has been operationalized by two factors: the level of product-specific expertise and the availability of an articulated ideal point; and (4) the decision goal reflects the degree to which individuals aim to minimize the cognitive effort involved in making a choice among the options contained in the available assortments and is operationalized by two measures: decision intent (buying vs browsing) and decision focus (choosing an assortment vs. choosing a particular option)" (Chernev, Böckenholt, and Goodman 2015; p. 336). It is postulated that increasing levels of these four factors will result in higher choice overload and negative outcomes. Their results appear to support this.

Table 2-3: Examples of variables that influence the effect of assortment size on choice overload.

Extrinsic	**Intrinsic**
Choice Set Complexity	Preference Uncertainty
Presence of a dominant option	Product-specific expertise
Overall attractiveness of options	Availability of an articulated ideal product characteristic
Aligned features between options	
Complementary features between options	
Decision Task Difficulty	Decision Goal
Time constraints	Decision intent (buying vs. browsing)
Decision accountability	Decision focus (choosing an assortment vs. choosing a particular option)
Number of attributes describing each option	Level of Construal (high vs. low)
Presentation format	

Choice overload is a source of distress for consumers. When choice overload occurs consistently in all domains of one's life, then it can become a serious problem for the person in terms of their psychological well-being. Recommenders can either mitigate consumers against the overwhelming choices they face in the many facets of their life or they can exacerbate the negative effects (depending on the characteristics of the system and consumer). The number of choices that consumers, and most decision makers in general, face is increasing in all domains and so too are recommenders as illustrated in section **2.1.1** (for example, in government, healthcare, education, social relationships, entertainment, shopping, etc.). Recommender systems may do things such as advise judges on bail decisions (Schwartzbach n.d.) (judges in Kentucky are required by law to consult a bail algorithm (Simonite 2019)), advise nurses on creating care plans for patients (Duan, Street, and Xu 2011), or even advise banks on a customer's credit risk (Citron 2014). Therefore, the study of recommenders' impact on consumers, and decision makers in general, across various domains is a prudent area of research, not just for increasing business profitability, but also for safeguarding consumers' sovereignty and well-being (Banker and Khetani 2019).

2.2.2 Consumer Empowerment

Consumers' access to information and freedom to choose is increasing across a variety of dimensions: product information, alternative options, new categories, greater variety, customization options, etc. Social media, review websites, and e-commerce platforms are continually improving to allow consumers to find, create, exchange, and compare information to help make better decisions. Freedom of choice and the expansion of consumers' information capabilities are the two driving forces of what has been called "consumer empowerment." Broniarczyk and Griffin (2014) review the literature to explore how consumer empowerment create sources of choice difficulty. In addition, they explore how decisions aids, such as recommender systems, can mitigate or exacerbate choice difficulty as a result of consumer empowerment.

Broniarczyk and Griffin (2014) identify three primary sources of decision difficulty: task complexity (information load and information uncertainty), tradeoff difficulty (conflict and emotional difficulty), and preference uncertainty. Reviewing the extant literature on choice difficulty, they summarize how consumer empowerment heightens the effects of the three primary sources of difficulty in a table which has been adopted in **Table 2-4**.

Three outcome categories of choice difficulty are also identified: avoiding choice, simplifying choice, post-choice consequences. Whether consumer empowerment facilitates the choice difficulty that affects these outcomes is proposed to be moderated by a number of variables: consumer knowledge, information type and organization (by-attribute vs. by-alternative format, visual vs. verbal format, attribute alignability, and information organization), mental representations (mental construal and metacogntitive expectations), and maximization tendencies. Clearly, there is overlap between the information type and organization moderators and the characteristics of recommender systems, suggesting that recommenders can be facilitators of choice difficulty. Broniarczyk and Griffin (2014) proceed to discuss the benefits and cautions of employing decision aids surmised in **Table 2-5** that has been adopted from their work.

Table 2-4: Effects of consumer empowerment (choice freedom and information expansion) on sources of decision difficulty (task complexity, tradeoff difficulty, and preference uncertainty) adopted from (Broniarczyk and Griffin 2014).

Choice Freedom	**Information Expansion**
Task Complexity ► Extensive choice in various domains associated with higher information overload ► Difficulty compounded when consumers elect to choose from large assortment or increase size of self-generated option set ► Increased customization possibilities can increase information overload, especially with by-alternative presentation format.	*Task Complexity* ► Necessity of evaluate extensive information sources adds to complexity, particularly with high levels of skepticism ► Information sources may disagree and diagnosticity is often incorrectly judged
Tradeoff Difficulty ► Extensive choice and customization heighten conflict, particularly when options are nonalignable ► Consequential choices associated with elevated difficulty	*Tradeoff Difficulty* ► Reviews with both pros and cons can increase conflict, highlighting difficulty in resolving tradeoffs ► Information rich media sources increase mental simulation of consumption experience, leading to option attachment and greater feelings of loss for non-chosen options
Preference Uncertainty ► Small differences in option attractiveness magnify preference uncertainty and increase decision difficulty ► Inability to match attribute combination to desired benefit in customization increases preference uncertainty	*Preference Uncertainty* ► Although WOM is sought more when prefences are uncertain, it does not necessarily enhance ability to predict consumption experience ► Even recommendations consistent with preferences can decrease consumer choice confidence if choice justification differs from one's own reason for the choice

Table 2-5: Benefits and caution of decision aids adopted from (Broniarczyk and Griffin 2014).

	Benefits	**Cautions**
Preference Learning Tools	Aid consumers in understanding attributes, clarifying preferences, ascertaining across attribute importance trade-offs Aid consumers in understanding link between attributes and benefits	Can be frustrating and further contribute to difficulty if not easy and quick to use
Product Filtering Tools	Enable consumers to organize product option set consistent with their own mental representations and decision tasks	Attributes used to sort product set may be deemphasized by consumers in later choice
Comparison Tools	Reduce difficulty of comparing products, decreasing size and increasing quality of consideration set and choice	Increased attachment to options selected for comparison can lead to a sense of loss for non-chosen options
Recommendations	Reduce search effort, decrease size yet increase quality of consideration set, and improve purchase quality	Lowered search costs may lead to oversearch and worse choices
Defaults	Reduce cognitive effort by eliminating need to engage in deliberative processing Systematically increase choice likelihood of particular options, often the default option	Serve as implicit recommendation or reference point which is not neutral Consumers who are skeptical of default intention will be less likely to follow
Choice Delegation	Eliminates need for decision-making and alleviates cognitive tradeoffs	Consumers are reluctant to delegate decision autonomy Delegation can deplete consumers' self-regulatory resources more than making decision independently

2.2.3 Choice-Making Effort and Confidence

Many studies have examined the influence of recommender systems on choice-making effort and confidence. The findings of most of these studies were summarized by Xiao and Benbasat (2007, 2014), who develop 23 propositions answer three research questions on how recommendation agents (RAs) affect consumer decision making processes and outcomes: (1) How does RA use influence consumer decision making processes and outcomes? (2) How do the characteristics of RAs influence consumer decision making processes and outcomes? (3) How do other factors (i.e., factors related to user, product, and user-RA interaction) moderate the effects of RA characteristics on consumer decision making processes and outcomes? In exploring these questions, they uncovered many experiments that showed a statistically significant effect of recommender use on effort as well as confidence. Outcomes used to measure effort include extent of product search, actual task time, perceived task time, amount of user input, perceived cognitive effort. Outcomes used to measure confidence include confidence in decision and switching final choice.

Although there have been tens of studies on how recommender systems affect choice-making (Xiao and Benbasat 2007, 2014), very few have examined how the influence of the number of recommendations impact choice difficulty, especially in terms of effort and confidence. Confidence, and especially how it is influenced by uncertainty, has also been studied in both group (Sniezek 1992) and individual choice-making settings (Sniezek, Paese, and Switzer III 1990). “Confidence refers to consumers’ impression of the quality of their judgments and is largely a function of the perceived clarity or correctness of consumers' preferences and beliefs" (Tsai and McGill 2011).

Diehl (2005) examined the influence of the number of recommendations on decision quality. When subjects were presented with the top 50 recommendations versus the top 15 recommendations, they searched a greater number of option and experienced a lower quality consideration sets, poorer product choices, and lesser selectivity. Punj and Moore (2007) conducted a 2 ("smart" vs. "knowledgeable" recommender) x 2 (many vs. few alternatives) x 2 (more vs. less time available) where they examined the effects on number of alternatives examined, number of search iterations, size of final consideration set, total set of alternatives considered, perceived cognitive effort, perceived product fit, satisfaction with search. The findings of the study primarily indicate that the type of feedback provided by the recommender ("smart" vs "knowledgeable") can interact with the number of alternatives available to affect search behaviors. Greater search behavior is likely, but not necessarily, associated with lesser confidence in choice.

Aljukhadar, Senecal, and Daoust (2012) investigated how recommenders can be used to cope with information overload. Their experiment manipulated the number of alternatives and number of attributes for each alternative. Their results suggest the perception of information overload from a recommender can contribute to choice quality, confidence, and perceived interactivity. Bollen et al. (2010) also investigated how choice overload can occur in recommender systems. Their experiment investigate the effects of recommendation set size (5 or 20) and set quality (low or high). They found that large recommendation sets contained only attractive items (as perceived by users) resulted in greater information search and decision time compared to a large set contained some unattractive items. Similarly Oulasvirta, Hukkinen, and Schwartz (2009) examined how the number of search results affects choice behavior. In their experiment, subjects shown a search scenario and were required to choose the best result within 30 seconds. In one condition subjects were shown only 6 search results, while in the other condition they were shown 24. They found that having to choose from smaller set of results yielded both higher subjective satisfaction with the choice and greater confidence in its correctness.

The aforementioned studies serve to illustrate the possibility that the number of alternatives suggested by a recommender can influence choice-making effort and confidence and this likely occurs due to changes in perceived choice difficulty. In regard to confidence, two closely related concepts are decision freedom. Perceived decision freedom has been studied in the context of soft drink selection where a greater number of alternatives was found to result in greater perceived decision freedom (Reibstein, Youngblood, and Fromkin 1975; Walton et al. 1979). However, the time taken to make the decision increased (Walton et al. 1979). These results suggest that when consumer perceive greater freedom they may feel inclined search more, although the search may not yield better post-consumption evaluations.

Decision freedom with the arousal of dissonance (Reibstein, Youngblood, and Fromkin 1975; Walton et al. 1979). "Dissonance appears to be much more readily aroused when people believe their actions are self-determined than when they do not…" (Steiner 1970). Dissonance may also be aroused through the interaction of customer effort and expectation (Cardozo 1965). Therefore, if a recommender can arouse dissonance, whether by altering perceptions of size of the choice set or the amount customers' effort, it may be because the customer is experiencing a greater sense of self-determination and thus autonomy.

The findings of Cardozo (1965) indicate that effort induces dissonance through an interaction with expectations (low vs. high) regarding the quality of the product (choice). In his experiment expectations were manipulated using by the average price (low vs. high) of the product. Subjects in the high expectations group, who put in considerably more effort in the shopping task, reported higher evaluations for the product they received than those who put in less effort. Cardozo (1965) explained that expending more effort made the outcome of the shopping task more important to the subjects. In other words, the customer felt more invested in the outcome of making the choice, and so, they experienced dissonance to reduce the disparity between their expectations and the product they received, which was of a low average price. These findings suggest that although the number of products may influence customer effort, the post-choice outcome may ultimately be influenced a great deal by the expectations of the customer, which could occur as a result of price (Cardozo 1965) or assortment size (customers expecting a greater likelihood of finding a product that matches their preferences.

From the studies and literature reviews mentioned in this section, it is clear that both number of alternatives and the simple use of a recommender can influence choice-making effort, confidence, and satisfaction. However, the extent to which the number of recommendations alters the perception of the assortment size, and thus these outcomes, is not clear. Moreover, if there is a change in the perception of assortment, how are the outcomes moderated by the characteristics of the consumer and the product? This study will investigate these effects.

2.3 Hypotheses and Research Model

Much of the literature on choice overload puts forth the idea that too large of an assortment can negatively impact customers' satisfaction with their choice and shopping experience (although not always). Too many options coupled with too much information about the alternatives results in a more difficult choice scenario. Additionally, preference uncertainty, as result of low familiarity/product knowledge, may result in less confidence in making the "best" choice. Consumers desire to be confident in their choices, and when overloaded with information and choices, may defer to recommended options to alleviate the cognitive load of comparing all options and feel more confident about their choice (Aljukhadar, Senecal, and Daoust 2012). Aljukhadar, Senecal, and Daoust (2012) explored how the number of alternatives and product attributes impacted recommender use and choice quality. They found that the number of alternatives and product attributes presented to subjects had a statistically significant effect on perceived overload. Goodman et al. (2013) also found "evidence that recommendation signs create preference conflict for consumers with more developed prederences, leading these consumers to form larger consideration sets and ultimately experience more difficulty from the decision-making process" (p. 165).

H1. A greater number of recommendations on product pages results in greater perceptions of assortment size.

H2. Greater perceptions of assortment size result in greater perceptions of choice difficulty.

One of the primary ideas being explored in this study is whether the mere presence of recommendations can influence customers' perceptions of assortment size, and if so, how many recommendations will it take to increase these perceptions to the degree that the negative outcomes of choice overload manifest (e.g., taking greater time and effort to choose, less confidence in choosing, and less satisfaction with the shopping experience).

In a study of search engine use, Oulasvirta, Hukkinen, and Schwartz (2009) investigated whether the number of search results from a search engine could result in choice overload. Their study showed that “having to choose from six results yielded both higher subjective satisfaction with the choice and greater confidence in its correctness than when there were 24 items on the results page” (p. 516). Bollen et al. (2010) investigate the effects of recommendation set size (5 vs 20) and recommendation set quality (low vs high) on recommendation set attractiveness, choice difficulty, and satisfcation with the chosen item. Their results suggests that increased recommendation set size does result in more choice difficulty and, depending on the characteristics of the set, does not increase satisfaction. Subjects also expended greater effort inspecting more items with larger recommendation sets. Greater search behavior has also been associated with less confidence (Diehl 2005; Punj and Moore 2007), which makes sense: a customer spending more time comparing options could also mean that customer is not as sure about which option they would like. Sharma and Nair (2017) found that the likelihood of subjects switching their choice (an indication of low confidence) increases almost linerly as the number of options increases from 6 to 36. Additionally, the results of a meta-analysis showed effects of assortment size on choice overload to be significant, resulting in greater effort expendended, lesser choice confidence, and lesser satisfaction. This study will test whether six recommendations can ellicit these effects. Six recommendations appears to have been about the minimum tested in prior studies manipulating the number of recommendations. Will the effects occur with an even lower number of recommendations? To consider this possibility, this study will also test whether three recommendations can ellicit these effects.

H3. Greater perceptions of choice difficulty result in greater choice-making effort.

H4. Greater perceptions of choice difficulty result in lesser choice-making confidence.

H5. Greater choice-making effort results in lesser choice-making satisfaction.

H6. Greater choice-making confidence results in greater choice-making satisfaction.

Although the actual assortment of products on an e-commerce site does not usually change during a shopping session, repeated exposure to recommended products on focal product pages may expand the awareness of the options available and thus perception of assortment size. Additionally, when customers become aware of more options, they may begin to seriously consider a greater number of options (a larger consideration set) for their final purchase choice. In fact, the likelihood of a customer bringing another option into their consideration set may be influenced by the strength and other characteristics of the recommendation itself. When the consideration set becomes too large, the customer can feel greater uncertainty and difficulty in committing to a final choice.

On the other hand, the notion of recommenders increasing a customer's consideration set runs counter to the findings of prior research: "RA [Recommendation Agent] use reduces the extent of the product search by reducing the totals size of alternative sets processed by the users as well as the size of the search set, in-depth search set, and consideration set" (Xiao and Benbasat 2014). However, it seems likely that when a customer is unfamiliar with the product category they may rely on the recommendations as a tool for exploration to find more alternatives for consideration. This may especially be the case for a maximizing type customer. Therefore, customers with low product knowledge may perceive greater choice difficulty from a larger perceived assortment size than customer with high product knowledge. As a consequence, they may expend greater effort and feel less confident about their choice than customer with high product knowledge.

H7. Higher product knowledge lessens the positive influence of perceptions of choice-making difficulty on choice-making effort.

H8. Higher product knowledge lessens the negative influence of perceptions of choice-making difficulty on choice-making confidence.

Diehl and Poynor (2010) investigate the effects of assortment size and expectations on choice satisfaction. Their study finds that "even when consumers make a purchase, the same item may generate lower satisfaction when chosen from a larger rather than smaller assortment" (p. 312). They explain their results in terms of expectation-disconfirmation in a manner that contradicts earlier findings by Cardozo (1965). Cardozo (1965) induced subjects to expend more (vs. less) effort when searching through a catalog of pens and set expectations depending on the average value of the pens (low vs. high). Subjects in the high effort, high expectation group who received a pen of low value experienced positive disconfirmation, due to greater effort invested, and thus were more satisfied with the pen than those in the low effort, high expectation group. In the studies by Diehl and Poynor (2010) expectation is manipulated by changing the assortment size; they theorize that increasing assortment size also increases consumers' expectations that the assortment will be able to provide a closer match to their preferences. When subjects chose from larger assortments, they experienced negative disconfirmation and were less satisfied with their choice. Necessarily, choosing from a larger assortment takes more effort, so why the contradictory findings? Perhaps the interaction of expectation and effort depends on what the expectations are set about. In one case the expectations were of a match between the preferences of the subject and the product, while in the other case it was the monetary value of the product. Regardless, both studies suggest that that effort influences satisfaction and increased effort can be induced through assortment size.

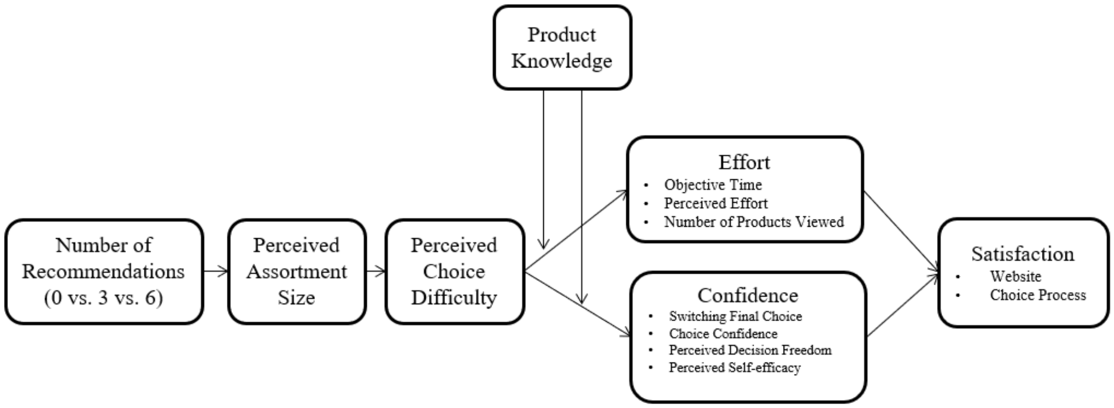

Figure 2-2: The research model to be tested in this study.

CHAPTER 3

METHODS

3.1 Experimental Design

An experiment will be used to test the model presented in **Figure 2-2**. Subjects will participate in a shopping task on a website that mimics the experience of shopping on a real e-commerce website. To test the idea of whether more recommendations can create choice overload, subjects will be split into three groups that are each exposed to a different number of recommendations on the individual product pages: 0 vs. 3 vs. 6 recommendations.

Subjected will be asked to imagine that they have received a $25 gift card for “mastercraftpens.com” and have now decided to redeem their card buy purchasing a fancy pen. To incentivize the subjects to make a choice as if they are really making a purchase, they will be given the opportunity to opt-in to really winning the pen of their choice. If selected as a winner, the subject will have the pen they chose shipped to their home address.

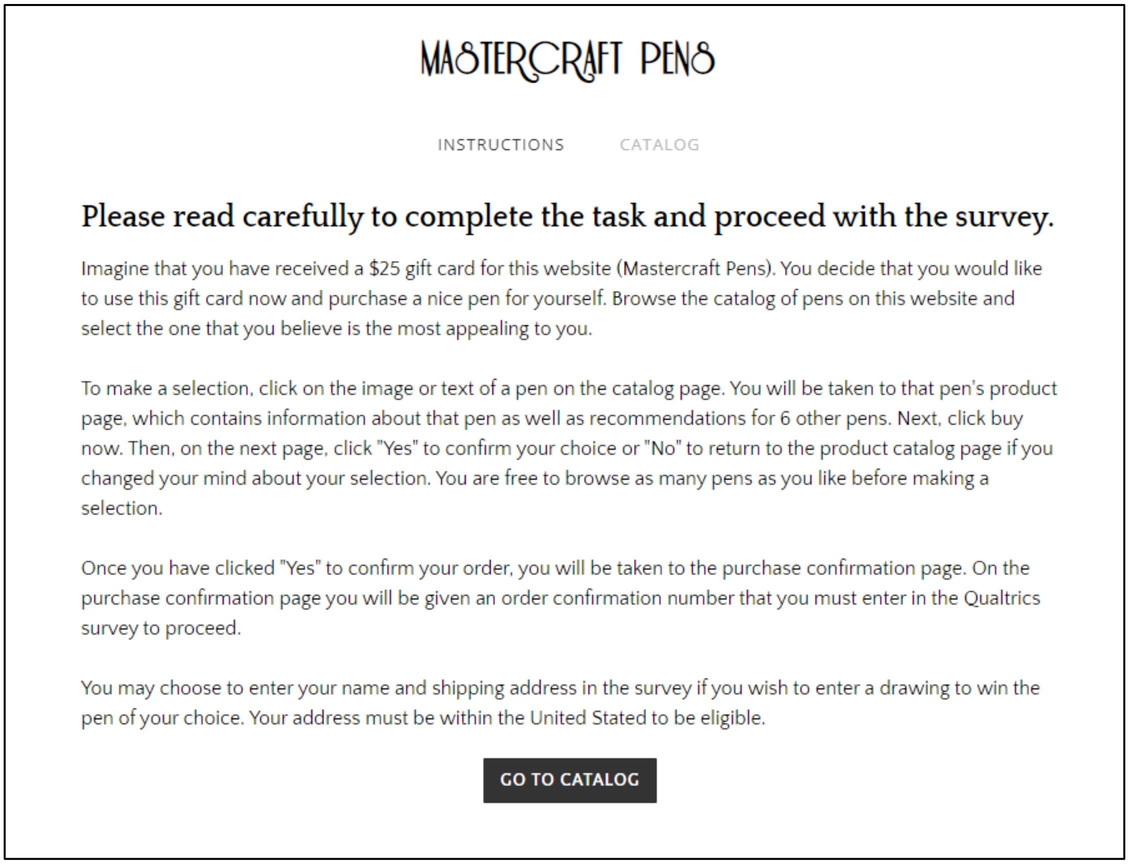

Figure 3-1: The instructions page of the website. The subjects will be informed of the number recommendations they would see on the product pages depending on which experimental group they are in.

The website will be built using the free website builder Weebly. The first page on the website will be a set of instructions for the respondents to follow in order to complete the shopping task and survey. After reading the instructions, subjects will go to the next page: the product catalogue. On the product catalogue page, the name, price, and an image of each pen will be displayed in a grid format. Subjects may select any pen on the page to proceed to its product page and that contains a description and enlarged image of the pen. Depending on which treatment group they are in, subjects will also be able shown either six, three, or no recommendations for other pens in the catalogue on each product page.

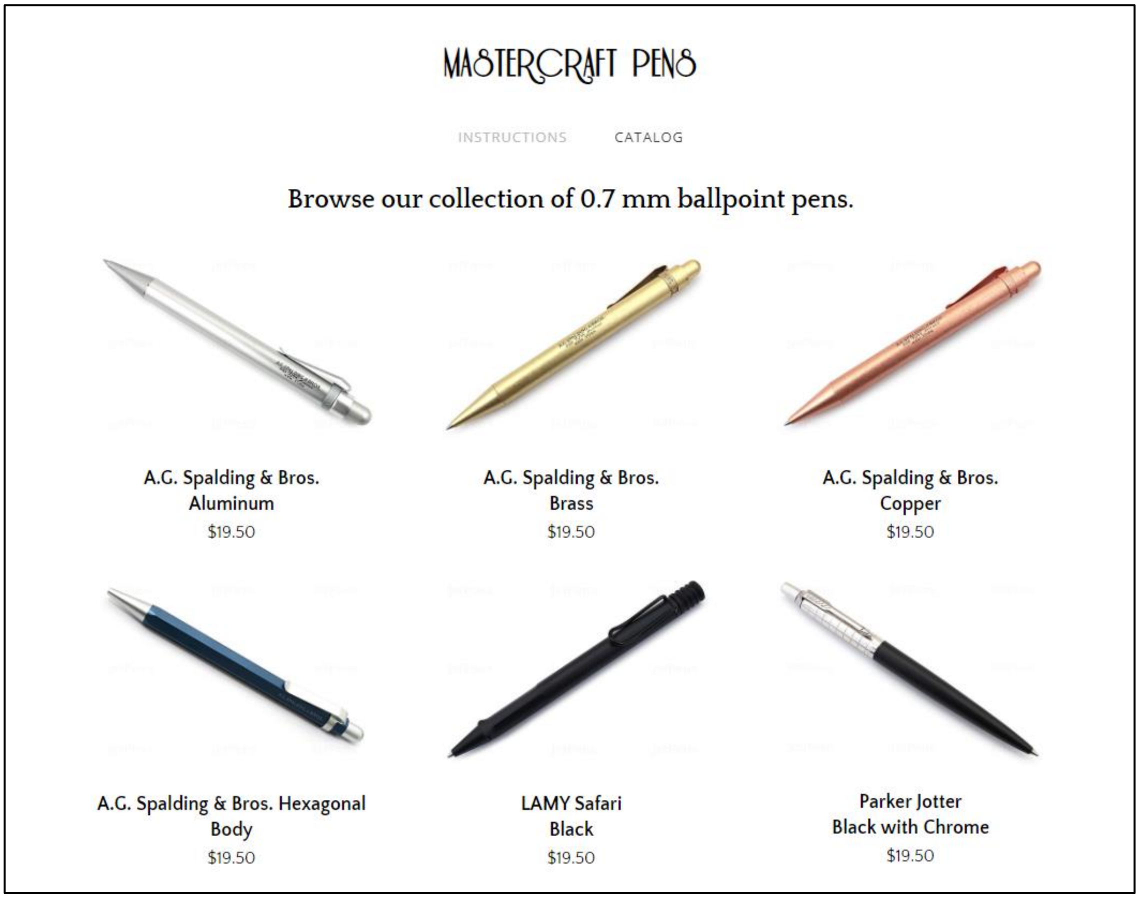

Figure 3-2: The product catalogue page. Thirty pens are displayed in a grid format. Clicking on the pen image or text will take the respondent to that pen's product page.

Recommendations will be listed below the details of the focal product on each product page and displayed in a grid format showing the picture, name, and price for each recommended pen. Which products are recommended on which pages will be determined at random; however, all the subjects in the treatment group will see the same recommendations. The recommendation list will be labeled with "3 Recommendations Available For You Below." The price will be held constant across all pens at $19.50.

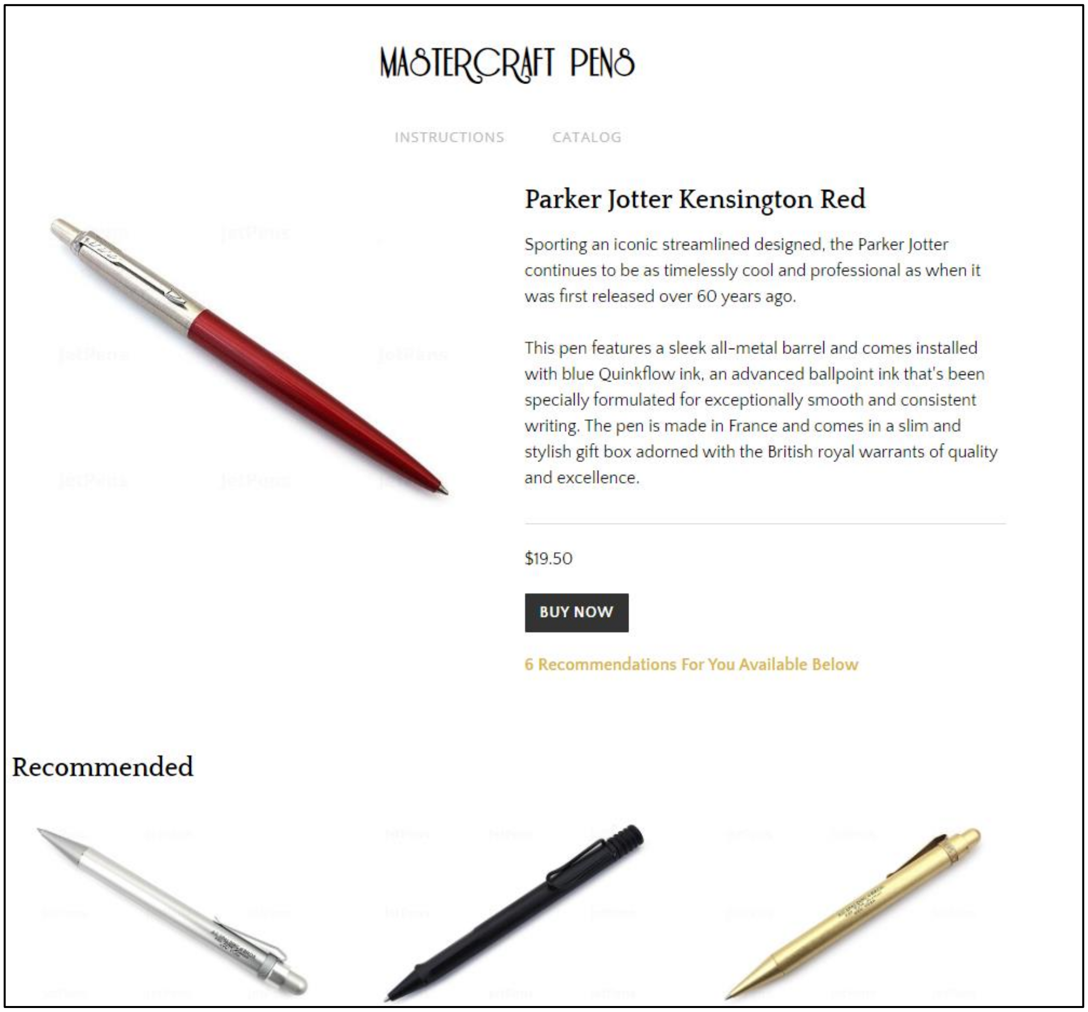

Figure 3-3: The product page containing the pen's description, price, and recommendations below in a grid format. Clicking on a recommended pen takes the user to that pen's product page which has more recommendations. No recommendations are in the control condition and the message "No Recommendations For You Are Currently Available" will be displayed.

Subjects may navigate between the catalogue page and product pages freely. Once they have selected their final pen for purchase, subjects may proceed to the checkout page. At the checkout page they will be asked whether they would like to confirm their order or go back to make a different choice. After confirming their order, subjects may then take the survey asking them about their choice experience. The survey will capture the constructs to be tested in the model. Subjects will be split depending on high or low product knowledge and this variable will be used as a moderator in the analysis.

Google analytics will be used to track subjects' behavior and compare them between the three versions of the site (0, 3, and 6 recommendations). Google analytics will provide aggregate data on the number of page views, the average time spent on the site, and how many subjects switched their final choice. These objective measurements will be used in the analysis to provide additional insights on subjects' self-reported data. Pretest data to ensure the website and survey function will be collected from Amazon mTurk. The final data set will consist of subjects from a Qualtrics panel representative of the general U.S. consumer population.

3.2 Pre-test Procedures

Responses from a small sample of subjects will be obtained for pre-testing purposes before the main study is conducted. The responses will be collected via Amazon's mTurk service. A manipulation check will be performed to assess whether the subjects are observing the correct number of recommendations on product pages. The manipulation checks addresses a limitation of prior studies which did not report a test for differences in the number of perceived recommendations/alternatives in each experimental group or if each group perceived the correct number of recommendations/alternatives (Aljukhadar, Senecal, and Daoust 2012; Bollen et al. 2010; Goodman et al. 2013; Lajos, Chattopadhyay, and Sengupta 2009; Oulasvirta, Hukkinen, and Schwartz 2009; Tsai and McGill 2011).

Subjects will complete the shopping task and respond to the following items after responding to the dependent variables in the survey. Subjects in all groups will be presented with these same two checks and will choose one of three options to respond to each check. Cross tabulation tables will be used to identify significant differences in the frequency of responses for each option for each group.

Number of Observed Recommendations on Product Page

1. After clicking on a pen from the product catalog, how many product recommendations did you see below that pen's description? (0, 3, or 6)

Perceptions of Recommendation List Size

2. After clicking on a pen from the product catalog, there were (no / few / many) product recommendations below that pen's description?
3. What the pen you chose recommended by the website? (no / yes)

3.3 Measures

Measures related to the following constructs are used in this study. Multiple scales are used to capture some of the constructs, but only one scale from each category is reported in the test of hypotheses for this study (marked by *). The full text of the survey items is available in **Appendix A**.

- Product Knowledge
    - Subjective Product Knowledge (Flynn and Goldsmith 1999)*
    - Product Involvement (Hu and Krishen 2019)
- Satisfaction

  - Customer Satisfaction with Website (Hostler et al. 2011; American Consumer Satisfaction Index)
  - Online Shopping Convenience (Jiang, Yang, and Jun 2013)
  - Decision Process Satisfaction (Hu and Krishen 2019)*
- Choice-making Effort
  - Perceived Decision Effort (Xu 2017)*
- Choice-making Confidence
  - Perceived Self-efficacy (Ajzen 2002)*
  - Perceived Decision Freedom (Reibstein, Youngblood, and Fromkin 1975; Walton et al. 1979)
  - Perceived Decision Quality (Xu2017)
  - Choice Confidence (Aljukhadar 2017)
- Choice-making Difficulty
  - Decision Difficulty (Hu and Krishen 2019)
  - Perceived Decision Making Difficulty (Goodman2012)*
  - Perceived Information Overload (Aljukhadar2017)
  - Information Overload (Hu and Krishen 2019)
  - Perceived Choice Overload (Aljukhadar, Senecal, and Daoust 2012)
- Perceived Assortment Size
  - Perceived Assortment Size (Goodman et al. 2013)*

All constructs were measured on 7-point Likert scales anchored by strongly disagree and strongly agree. Additionally, an attention check is used to ensure that respondents carefully read the items in the survey. Google Analytics is used to capture objective behavior data on users' session duration (effort), the number of pages they visited (effort), and the number of users who changed their final choice (confidence in choice). Demographics information on age, sex, and online shopping habits are also captured. Lastly, respondents are allowed to comment why they made the choice they did and their experience completing the shopping task.

3.4 Analyses

A pre-test will confirm whether subjects are able to perceive the correct number of recommendations and if they feel that this number is high. Depending on their responses the number of recommendations in the treatment group may be increased before the full data collection. Subjects from the full data collection with suspicious responses will be removed from the data set. One-way ANOVA, chi-squared tests, simple regression, multiple regression, and hierarchical regression are used to test the hypotheses. SEM will not be used as the continuous variable moderator (subjective product knowledge) to be tested and the experimental nature of this study would make interpretation difficult. The characteristics of the data and results of the analyses are reported in the next chapter.

CHAPTER 4

RESULTS

4.1 Pre-test Results

Twenty five usable observations were collected via mTurk. The purpose of the pre-test was to determine how well user payed attention to the experimental manipulation. Nine of the 25 subjects did not report seeing the correct number of recommendations: 3 reported seeing recommendations when there were none, 3 reported seeing no recommendations were there were some, and 3 reported seeing the wrong number of recommendations (e.g., seeing 3 when there were 6 present). Cross tabulations for the number of recommendations shown to subjects and the number of recommendations subjects reported seeing (both quantitatively and qualitatively) are reported in below. Statistically significant chi-squared tests suggest an association below the number of recommendation subjects are shown and what they report seeing.

Table 4-1: Cross tabulation of the number of recommendations pre-test subjects reported seeing (rows) and the number of recommandations they were shown (columns). The number of subjects is shown in each cell.

	control	three	six	Total
Reported 0	6	2	1	9
Reported 3	0	4	0	44
Reported 6	3	3	6	12
Total	9	7	9	25

Table 4-2: The chi-squred test suggests that there is a strong association between the number of recommendations shown to pre-test subjects and the number they report seeing.

	Value	df	p-value
Pearson chi-square	13.735	4	0.008
Likelihood ratio	14.371	4	0.008

Table 4-3: Cross tabulation of the qualitative number of recommendations pre-test subjects reported seeing (rows) and the number of recommandations they were shown (columns). The number of subjects is shown in each cell.

	control	three	six	Total
Reported “no”	6	3	1	10
Reported “few”	0	6	4	10
Reported “many”	3	0	2	5
Total	9	9	7	25

Table 4-4: The chi-squred test suggests that there is a strong association between the number of recommendations shown to pre-test subjects and the qualitative quantity they report seeing.

	Value	df	p-value
Pearson chi-square	11.429	4	0.022
Likelihood ratio	16.452	4	0.002

However, it appears that some users simply do not pay enough attention to correctly remember how many recommendations they receive. And strangely, more users reported seeing “many” recommendations for the control condition that in the six condition (**Table 4-3**). On mobile devices, users are required to scroll down to see the recommendations when viewing pages, which means that users who do not scroll down simply will not see any. Therefore, the product pages and experiment instructions were adjusted to explicitly state the number of recommendations subjects would see, with the intention that subjects would be more likely to pay attention to the recommendations (**Figure 3-3**). The manipulation check question wording was adjusted as well (see section 3.2).

Google Analytics reported only 20 unique users for the pre-test; some site visits were not captured or excluded. This could be because the user is using a browser (e.g., Brave) or software (e.g., Ghostery) to block internet trackers and, therefore, they would be invisible to Google Analytics. Users who were repeat visitors, which while still captured, were excluded from the analysis to remove duplicate respondents. Google Analytics reported 8, 6, and 6 users for the zero (control), three, and six recommendations groups, respectively. Subjects website behavior is reported in **Table 4-5** below.

Table 4-5: Summary of pilot test subject behavior data captured by Google Analytics.

	Users	**Avg. Session Duration**	**Avg. Pages / Session**	**Changed Final Choice**
Control	8	3m 8s	7.88	0
Three	6	2m 8s	8.17	0
Six	6	2m 17s	7	1

In the control group, on average, users spent 3 minutes and 8 seconds (min = 41s, max = 7m 44s, med = 1m 55s) on the website and visited 7.88 pages. Zero users changed their minds about the final choice. In the three group, on average, users spent 2 minutes and 8 seconds (min = 33s, max = 6m 49s, med = 1m 18s) on the website and visited 8.17

pages. Zero users changed their minds about the final choice. In the six group, on average, users spent 2 minutes and 17 seconds (min = 29s, max = 6m 55s, med = 1m 48s) on the website and visited 7.00 pages. One user changed their mind about the final choice.

In response to the question "What would have improved your shopping experience on the website?" one subject commented, "have fewer pen choices" and another "having a smaller selection would have made it quicker." These comments suggest that some users prefer having less options. One user in the control group commented "I didn't see any recommendations, but to be honest, I had made up my mind and was happy with what I selected." Most subjects responded positively to the open ended questions about the website and survey experience, and none reported that any part of the shopping task or survey was difficult to understand.

4.2 Data Treatment

Observations from the final data set were filtered in a number of ways to ensure data quality. First, two attention checks asking respondents to select "Strongly Agree" or be removed were used in the survey to catch and remove careless subjects. In addition, two items as part of the manipulation check were set up in Qualtrics to filter out respondents not paying attention. Respondents who answered that they saw "0" recommendations AND "few" or "many" recommendations were filtered. Likewise, respondents who answered that they saw "3" or "6" recommendations AND "no" recommendations were also filtered.

Second, subjects with disingenuous responses were also filtered. This included subjects who entered unrealistic responses for how much time in minutes they believed that they spent on the website (e.g., 1000) or how many product pages they believed that they visited (e.g., 100). The falsity of this information could be verified by checking whether the numbers reported by subjects went far beyond what was observed for any subject in Google Analytics and the Qualtrics survey time measurements (specifically the time they spent on the page where they were given a link to the shopping website and asked to enter the correct confirmation code to proceed to the survey). Subjects who were not able to remember at least a name or color for their pen were also filtered. Additionally, subjects who wrote responses in languages other than English or gave nonsense or unrelated responses to the open ended questions about the survey and experiment experience were filtered.

Third, steps were taken to filter speeders from the survey and website data sets. The survey contained a filter to automatically catch and remove respondents who taking less than half of the median time to complete the survey from the survey data set. But because respondents could not have their website behavior (recorded by Google Analytics) linked with their survey responses, and therefore, unfortunately, could not be identified and removed from the website behavior data set.

The data captured by Google Analytics included users who were filtered from the survey data set. This resulted in a large discrepancy between the number of users reported in analytics and the number of subjects available in the survey data set. The discrepancy occurred because of subjects who failed the manipulation checks, who failed the attention checks, who were speeders, who gave incomplete responses, as well as those who were filtered out during the data treatment. Unfortunately, with the methodology implemented in this study, there was no way to match respondents from the survey with the google analytics data and, thus, the two could not be directly compared. However, users in analytics can be segmented based on their behavior (e.g., number of sessions, number of pages visited, average session duration, whether they visited a particular page, etc.). Users with more than one session and user who did not reach the purchase confirmation page were filtered from the final website data set. The final set of observations in the survey data set was 79, 83, and 97 for the 0, 3, and 6 groups respectively (N = 259). The final set of observations in the website data set was 147, 182, and 184 for the 0, 3, and 6 groups respectively (N = 483).

Table 4-6: The number of observations captured in the survey and website data sets.

	Survey Observations	**Website Observations**
Control	79	147
Three	83	182
Six	97	184
Total	259	483

4.3 Manipulation Check

Eighty one (31.3%) of the 259 respondents in the final data set failed to identify the correct number of recommendations shown on them (e.g., reporting they saw 3 recommendations when there were 6). Some subjects may have not scrolled down to see all the recommendations and thus may have not been able to correctly report them, or they otherwise simply misremembered. However, 47 of the 81 failed to correctly identify the presence or absence of recommendations (i.e., reporting that they saw recommendations when there were none or the opposite). This finding calls into question many studies on recommendations and assortment size who do not observe how carefully their subjects pay attention to the recommendations and number of alternatives.

A chi-squared test revealed a statistically significant association between the number of recommendations shown to subjects and the number of recommendations they reported seeing (**Table 4-7** and **Table 4-8**). Likewise, there was a statistically significant association between the number of recommendations subjects were shown and whether they reported seeing “no”, “few”, or “many” recommendations (**Table 4-9** and **Table 4-10**). Thus, the manipulation check results support the validity of the manipulation; all observations were retained in the final survey data set (N = 259).

Table 4-7: Cross tabulation of the number of recommendations subjects reported seeing (rows) and the number of recommendations they were shown (columns).

	control	**three**	**six**	**Total**
Reported 0	63	14	17	94
Reported 3	13	61	26	100
Reported 6	3	8	54	65
Total	79	83	97	259

Table 4-8: The chi-squred test suggests that there is a strong association between the number of recommendations shown to subjects and the number they report seeing.

	Value	**df**	**p-value**
Pearson chi-square	157.16	4	0.000
Likelihood ratio	149.77	4	0.000

Table 4-9: Cross tabulation of the qualitative quantity of recommendations subjects reported seeing (rows) and the number of recommandations they were shown (columns).

	control	three	six	Total
Reported "none"	63	17	14	94
Reported "few"	11	54	45	110
Reported "many"	5	15	35	55
Total	79	97	83	259

Table 4-10: The chi-squred test suggests that there is a strong association between the number of recommendations shown to subjects and the qualitative quantity they report seeing.

	Value	df	p-value
Pearson chi-square	103.352	4	0.000
Likelihood ratio	102.623	4	0.000

4.4 Sample Characteristics

The sample (N = 259) was representative of U.S. consumers, 112 (43.2%) are male, 147 (59.8%) are female, and the average age was 45.49 (min = 18, max = 78, std dev = 16.07). Qualtrics' built-in age quota captured the following counts for three age groups: 78 (30.1%) respondents report age between 18-34, 91 (35.1%) respondents report the 35-54 years bracket, and 90 (34.7%) report being 55+ years.

One hundred and thirty seven (52.9%) subjects completed the survey on desktop or laptop PCs and 122 (47.1%) completed it on mobile and tablet devices. This information is corroborated by the Analytics data, which shows similar splits (approximately 50-50) between users in each of the experimental groups.

Interestingly, 89 (34.4%) subjects provided a name and mailing address and 77 (29.7%) subjects provided an email address in order to have a chance at winning the pen of their choice. This information was provided voluntarily by subjects and was a completely option part of the survey. Many of the addresses are partial and there is no easy way to verify if they are truthful. However, this finding suggests that a good percentage of consumers are willing to relinquish their personal information for even a chance at receiving a benefit (in this case a $20 pen). Moreover, it suggests that at least some of the subjects were invested in the choice they made, even though this study did not entail making a real purchase.

Table 4-11: Characteristics of subjects captured in the survey data set.

	Male	**Female**	**Avg. Age**	**Desktop / Laptop**	**Mobile / Tablet**	**Provided Physical Address**	**Provided Email Address**
Subjects	112	147	45.49	137	122	89	77

4.5 Website Behavior Data

Google analytics data were captured for 147 users in the control group, 182 users in the three recommendations group, and 184 users in the six recommendations group. However, due to methodological challenges, the observations could not be matched with those in the survey data set and this data could not be used as intended for hypothesis testing.

The average session duration was 2m 49s for the control group, 2m 40s for the three group, and 2m 43s for the six group. However, this time also includes time spend on the website instructions page, choice confirmation page, and purchase confirmation page. In addition, users may have lingered on the site while completing the survey (e.g, kept it open in a browser tab), which would have added to users' session duration.

Table 4-12: Users average time spent on the experimental website.

	Users	Avg. Session Duration	Minimum	Medium	Maximum	Std. Dev
Control	147	2m 49s	14s	1m 36s	26m 59s	3m 48s
Three	182	2m 40s	8s	1m 41s	28m 15s	3m 20s
Six	184	2m 43s	7s	1m 26s	27m 28s	3m 36s

The average number of pageviews per session (user) was 8.23 for the control group, 8.05 for the three group, and 9.13 for the six group. This includes pageviews of the instructions page, choice confirmation page, purchase confirmation page, and all product pages on the website. The total number of product pages viewed was 539 for the control group, 696 for the three group, and 764 for the six group. The total number of unique product pageviews (i.e., a subject viewing the same product multiple times would only count as 1 pageview) and average time spent on each product page is summarized in **Table 4-13**. For comparison, how much time subjects believed they spent on the website and how many product pages they believed they visited in presented in **Table 4-14** and **Table 4-15**.

Table 4-13: Summary of subject behavior data captured by Google Analytics.

	Users	Avg. Session Duration	Avg. Pages / Session	Product Pageviews	Unique Product Pageviews	Avg. Time on Product Page	Changed Final Choice	
Control	147	2m 49s	8.23	539	318	23.04s	6	
Three	182	2m 40s	8.05	696	430	26.82s	12	
Six	184	2m 43s	9.13	764	428	20.11s	13	

Table 4-14: Subjects beliefs about how many minutes they spent on the website.

	Users	Mean	Minimum	Median	Maximum	Std. Dev
Control	79	4.75	1	4	20	3.72
Three	83	4.65	1	3	15	3.21
Six	97	4.59	1	4	20	3.13

Table 4-15: Subjects beliefs about how many product pages they visited on the website.

	Users	Mean	Minimum	Median	Maximum	Std. Dev
Control	79	2.85	1	2	30	4.41
Three	83	4.28	1	2	30	5.83
Six	97	2.51	1	2	15	2.41

4.6 Construct Loadings and Reliabilities

For each of the outcomes, several measures with largely similar items were employed. The reliabilities (Cronbach’s alpha) and item loadings for each scale are reported in **Table 4-16** below. Item loadings were obtained from a principle components analysis on each scale separately. Multi-item constructs were averaged to a single value for hypothesis testing. To simplify the analysis, hypothesis testing is reported using only one measure representing each category of outcome. Interestingly, support for the hypotheses can depend on which measures of the antecedents and outcomes are used in the analysis.

Table 4-16: Construct Reliabilities and Loadings.

Product Knowledge		
	Subjective Product Knowledge (α = .923)	
	Q4.1	0.908
	Q4.2	0.913
	Q4.3	0.904
	Q4.4	0.887
	Product Involvement (α = .848)	
	Q5.1	0.815
	Q5.2	0.849
	Q5.3	0.85
	Q5.4	0.81
Satisfaction		
	Customer Satisfaction with Website (α = .873)	
	Q6.1	0.861
	Q6.2	0.816
	Q6.3	0.82
	Q6.4	0.913
	Online Shopping Convenience	
	Q7.1	NA
	Decision Process Satisfaction (α = .731)	
	Q8.1	0.719
	Q8.2	0.826
	Q8.3	0.889
Choice Effort		
	Perceived Decision Effort (α = .802)	
	Q9.1	0.688
	Q9.2	0.925
	Q9.3	0.908

	Perceived Session Duration	
	Q2.7	NA
	Perceived Product Pages Visited	
	Q2.8	NA
Choice Confidence		
	Perceived Self-Efficacy (α = .864)	
	Q10.1	0.845
	Q10.2	0.864
	Q10.3	0.874
	Q10.4	0.791
	Perceived Decision Freedom	
	Q11.1	NA
	Choice Confidence (α = .632)	
	Q12.1	0.888
	Q12.2	0.887
	Q12.3	0.574
	Perceived Decision Quality (α = .898)	
	Q13.1	0.915
	Q13.2	0.897
	Q13.3	0.924
Choice Difficulty		
	Decision Difficulty (α = .679)	
	Q14.1	0.907
	Q14.2	0.902
	Q14.3	0.463
	Perceived Decision Difficulty (α = .870)	
	Q15.1	0.929
	Q15.2	0.868
	Q15.3	0.879
	Perceived Information Overload (α = .248)	
	Q16.1	0.756
	Q16.2	0.756
	Information Overload (α = .902)	
	Q17.1	0.916
	Q17.2	0.928
	Q17.3	0.902
	Perceived Choice Overload (α = .889)	
	Q18.1	0.919
	Q18.2	0.826
	Q18.3	0.872

Perceived Assortment Size		
	Perceived Assortment Size (α = .783)	
	Q19.1	0.693
	Q19.2	0.844
	Q19.3	0.849
	Q19.4	0.783

4.7 Hypothesis Testing

One-way **ANOVA** and cross tabulations were used to test hypothesis 1 (that a greater number of recommendations on product pages results in greater perceptions of assortment size). Although the cross-tabulation results suggest subjects perceive a larger number of recommendations when presented with more recommendations (**Table 4-7**, **Table 4-8**, **Table 4-9**, and **Table 4-10**), one-way **ANOVA** shows that perceptions of the website's overall assortment size did not differ between the experimental groups. Thus, hypothesis 1 is not supported.

Table 4-17: Descriptives and one-way **ANOVA** between the three experimental groups' perceptions of assortment size.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
control	79	5.5633	1.22178	.13746	5.2896	5.8370	1.00	7.00
three	83	5.5422	1.25050	.13726	5.2691	5.8152	1.50	7.00
six	97	5.5284	1.16138	.11792	5.2943	5.7624	2.00	7.00
Total	259	5.5434	1.20432	.07483	5.3961	5.6908	1.00	7.00

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.053	2	.027	.018	.982
Within Groups	374.145	256	1.462		
Total	374.199	258			

Simple regression was used to test hypothesis 2 (that greater perceptions of assortment size result in greater perceptions of choice difficulty) (**Table 4-18**). The association is positive but small and non-significant ($p = .456$). Therefore, hypothesis 2 is not supported. The results for the using other measures, which are not reported in this analysis may be significant depending on the measures of choice difficulty used.

Table 4-18: Simple regression of perceived decision difficulty on perceived assortment size.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.006	.414		4.847	.000	1.191	2.821
	PerAssortmentSize	.054	.073	.047	.746	.456	-.089	.198

Dependent Variable: PerDecDifficulty

Simple regression was also used to test hypotheses 3 (that greater perceptions of choice difficulty result in greater choice-making effort) and 4 (that greater perceptions of choice difficulty result in lesser choice-making confidence). As predicted, perceived decision difficulty has a significant positive influence on perceived decision-making effort (choice-making effort) (**Table 4-19**) and a significant negative influence on perceived self-efficacy (choice-making confidence) (**Table 4-20**). Thus, hypotheses 3 and 4 are supported.

Table 4-19: Simple regression of perceived decision effort on perceived decision difficulty.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	3.268	.155		21.141	.000	2.964	3.573
	PerDecDifficulty	.406	.057	.405	7.095	.000	.293	.518

Dependent Variable: PerDecEffort

Table 4-20: Simple regression of perceived self-efficacy on on perceived decision difficulty.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	6.534	.085		77.061	.000	6.367	6.701
	PerDecDifficulty	-.101	.031	-.196	-3.205	.002	-.162	-.039

Dependent Variable: PerSelfEfficacy

Multiple regression was used to test hypotheses 5 (that greater choice-making effort results in lesser choice-making satisfaction) and 6 (that greater choice-making confidence results in greater choice-making satisfaction) (**Table 4-21**). Perceived decision effort has a positive, but small and non-significant, relationship to decision process satisfaction. Perceived self-efficacy, on the other hand, shows a strong positive and significant relationship with decision-process satisfaction, suggesting that satisfaction is more the result of beliefs about control and skillfulness in decision making than of effort expended. Thus, hypothesis 5 not supported while hypothesis 6 is supported.

Table 4-21: Multiple regression of decision process satisfaction on perceived decision effot and perceived self-efficacy.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.632	.393		4.152	.000	.858	2.405
	PerDecEffort	.036	.032	.058	1.132	.259	-.026	.098
	PerSelfEfficacy	.684	.062	.571	11.109	.000	.563	.806

Dependent Variable: DecProcessSatis

Hierarchical regression was used to test hypotheses 7 (that higher product knowledge lessens the positive influence of perceptions of choice-making difficulty on choice-making effort) and 8 (that higher product knowledge lessens the negative influence of perceptions of choice-making difficulty on choice-making confidence) (**Table 4-22**). The results show that that there is a non-significant change in the model R squared when subjective product knowledge is added as a moderator with either perceived decision effort or perceived self-efficacy as an outcome. In the former case, the model R squared changed from 0.312 to 0.318, and in the latter case, the model R squared changed from 0.124 to 0.125). Therefore, neither hypothesis 7 nor 8 are supported.

Table 4-22: Heirarchical regression of perceived decision effort on perceived decision difficulty, subjective product knowledge, and the interaction between the two.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.558[a]	.312	.306	1.17763	.312	57.934	2	256	.000
2	.564[b]	.318	.310	1.17476	.006	2.251	1	255	.135

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4.205	.073		57.460	.000	4.061	4.349
	Zscore(PerDecDifficulty)	.590	.073	.418	8.048	.000	.446	.735
	Zscore(SubjProdKnowledge)	.544	.073	.385	7.414	.000	.399	.688
2	(Constant)	4.202	.073		57.540	.000	4.058	4.346
	Zscore(PerDecDifficulty)	.605	.074	.428	8.193	.000	.459	.750
	Zscore(SubjProdKnowledge)	.568	.075	.402	7.581	.000	.421	.716
	ModPerDiffProdKnowledge	-.087	.058	-.080	-1.500	.135	-.202	.027

a. Dependent Variable: PerDecEffort

Table 4-23: Heirarchical regression of perceived decision effort on perceived decision difficulty, subjective product knowledge, and the interaction between the two.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.352[a]	.124	.117	.67953	.124	18.094	2	256	.000
2	.354[b]	.125	.115	.68037	.001	.370	1	255	.544

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	6.302	.042		149.255	.000	6.219	6.385
	Zscore(PerDecDifficulty)	-.135	.042	-.186	-3.181	.002	-.218	-.051
	Zscore(SubjProdKnowledge)	.211	.042	.292	4.996	.000	.128	.295
2	(Constant)	6.303	.042		149.034	.000	6.220	6.386
	Zscore(PerDecDifficulty)	-.138	.043	-.191	-3.229	.001	-.222	-.054
	Zscore(SubjProdKnowledge)	.206	.043	.285	4.741	.000	.120	.291
	ModPerDiffProdKnowledge	.020	.034	.037	.608	.544	-.046	.087

a. Dependent Variable: PerSelfEfficacy

4.8 Summary of Findings

Several of the predicted effects were not observed. Regardless of the number of recommendations, subjects did not perceive a significant difference in the size of the assortment of pens on the website (**H1)**. Nor was a relationship observed between perceived assortment size and perceived decision difficulty (**H2**), which seems counter intuitive. The predicted effects of perceived decision difficulty on perceived decision effort (**H3** – a positive effect) and perceived self-efficacy (**H4** – a negative effect) were observed. The expected negative effect of perceived decision effort on decision process satisfaction was not observed (**H5**); however, a positive effect from perceived self-efficacy to perceived decision satisfaction was observed (**H6**). Although the result seems counter intuitive, the test for moderation did not provide support for the predicted moderating effects of subjective product knowledge on the relationships between perceived decision difficulty and perceived decision effort (**H7**) or perceived self-efficacy (**H8**). Methodological limitations prevented direct comparison subjects between self-reported and measured behavior; however, the website data does show some interesting insights that will be discussed in the next section.

Table 4-24: Heirarchical regression of perceived decision effort on perceived decision difficulty, subjective product knowledge, and the interaction between the two.

Hypothesis		**Support**
H1	A greater number of recommendations on product pages results in greater perceptions of assortment size.	✗
H2	Greater perceptions of assortment size result in greater perceptions of choice difficulty.	✗
H3	Greater perceptions of choice difficulty result in greater choice-making effort.	✓
H4	Greater perceptions of choice difficulty result in lesser choice-making confidence.	✓
H5	Greater choice-making effort results in lesser choice-making satisfaction.	✗
H6	Greater choice-making confidence results in greater choice-making satisfaction.	✓
H7	Higher product knowledge lessens the positive influence of perceptions of choice-making difficulty on choice-making effort.	✗
H8	Higher product knowledge lessens the negative influence of perceptions of choice-making difficulty on choice-making confidence.	✗

CHAPTER 5

DISCUSSION

5.1 Implications for Consumer Choice-Making

In general, most empirical research supports the view that recommenders affect consumers' behavior, feelings, and attitudes. The fact that recommenders have become a ubiquitous feature of online retail sites supports this view: recommenders are employed because they are effective and engaging consumers and increasing revenue. As discussed in Chapters 1 and 2, recommenders are being employed for many applications across many industries. Thus, there is a real need to more fully comprehend how recommenders will change the marketing environment in the coming decades, especially in regard to consumer choice.

Consumers rely on patterns to help them make choices. Recommenders represent a new component in consumers' day-to-day experiences; therefore, consumer's choice-making-patterns will be affected according to the characteristics of the recommenders they experience. The effects may be minimal or pronounced. Several common choice-making patterns were identified and discussed in Chapter 2. The choice-making pattern a consumer employs in a given circumstance depends on the type of product they are shopping for, their motives for seeking to purchase it, their familiarity with the product category, and variety of other factors. Ideally, recommenders can be developed to support whatever choice-making pattern a consumer might employ (i.e. make the choice-making process easier and more satisfying). Doing so would require the company employing the recommender to carefully consider of the characteristics of their customers. For example, the company should consider what the goals, motives, and experience of their target markets are and how these characteristics influence the way consumers perceive and approach their offerings. In other words, businesses should consider the patterns their customers exhibit and design the system to support those patterns, in both the generation and presentation of recommendations, to facilitate greater engagement, ease of use, and satisfaction with their offerings and the firm in general.

Engagement as a concept has been hotly debated but most scholars and practitioners agree that it consists of at least a behavioral component and potentially a psychological component. All behavior requires some degree of effort. Since recommenders affect choice-making patterns, they may increase behavior in some ways while decreasing it in others. For example, customers may spend more time watching shows on Netflix and purchasing more products on Amazon because of recommendations while also spending less time choosing between which shows to watch and which products to buy. In other words, the choices are easier to make and therefore happen more frequently. From a business perspective, recommenders should ideally decrease choice-making time while also increasing consumption and satisfaction.

5.1.1 Study Results

The findings from this study shed some light on how the presentation aspect of recommenders influences engagement in terms of the choice-making effort and confidence. The effects of the number of recommendations on choice difficulty, effort, confidence, and satisfaction were observed. It was hypothesized that increasing the number of recommendations presented to the customer would increase the choice difficulty and thus result in negative outcomes, such as greater effort and lesser confidence and satisfaction. In terms of effort, subjects appeared to spend about the same amount of time browsing the website between all three experimental groups. However, what is interesting is the subject's belief about how many product pages they visited.

Subjects in the three recommendation condition believe they visited about 2 more product pages on average than subjects in the other conditions. However, the website behavioral data shows that this not actually the case. In fact, the three group subjects visited the least number of pages per session on average, although the difference with the other two groups is not significant. What these results suggest is that possibly a few recommendations can increase perceptions of the difficulty of a task, while not altering the actual user behavior. If so, then two groups of users exhibiting the same behavior might differ in terms on their satisfaction with the experience which could affect other downstream outcomes, such as loyalty. Therefore, what is important for researchers and practitioners to consider is not just how to move consumers towards particular outcomes, but the way they reach those outcomes, or in other words, the user experience. User engagement does not necessarily equate to a positive user experience.

According to the choice overload model in **Figure 2-1**, increasing the number of options presented to users can result in choice overload. In this study, the effects of choice overload were not observed. There was not a significant difference between the three experimental groups in terms of either the perceived assortment size or choice difficulty. These findings are in agreement with the meta-analysis review in Chapter 2 that contests the validity of the choice overload theory. However, in this study, the total number of choices that subjects had were the same. They only differed in the number of recommendations they received. The thought behind this approach was that recommendations increase exposure to products and thus may influence the number of alternatives customers will consider for their final choice, and that a larger consideration set would increase choice overload and difficulty. However, subjects in all groups reported about the same difficulty in choice. Therefore, the results of this study suggest that simply exposing customers to more alternatives will not necessarily result in choice overload as has been suggested by other studies. Whether overload will occur must depend on how many alternatives the subject is seriously willing to consider, which is determined by the choice-making pattern they exhibit in that particular context.

From subjects' comments about why they chose the pen they did, the choices largely appeared to based on the attribute based, experience based, and trial and error based choice making patterns, which are presented as part of the ASPECT model in **Table 2-1**. For example, subjects chose a pen because they like the color or it reminded them a pen their mother used to have. The products which received the most views were the products displayed first on the page; all products were displayed in the same order on the catalog page for all groups. Therefore, we can conclude subjects' behavior was largely influence by order effects, likely owning to the fact that since this was not a real shopping scenario. Many subjects would simply choose the first item that appeared "good enough" (satisficing) so they could proceed with the survey. When subjects employ a satisficing strategy choice overload does is not likely to occur. Subjects may not even become aware of the total number of options available to them or pay attention to recommendations. Moreover, all subjects will see the task as equally difficult and thus any effects stemming from choice difficulty will not be affected by moderating variables, such as subjective product knowledge, which was exactly the case in this study. This may also explain why there was not a significant difference in the choice switching behavior observed between the groups.

Based on the observations from this study, we may speculate that choice overload is not simply a matter of the number of options presented to users as suggested by previous research. Instead, the occurrence of choice overload depends on the choice-making pattern and strategy subjects employ, which changes depending on the context of the choice situation. In this study, each experimental group largely appeared to exhibit satisficing behavior. When customers exhibit this type of behavior, overload and may not be observed no matter how large the choice set. In fact, overload may occur with even very small choice sets if the situation elicits, for example, a consequence-based choice making pattern where the subject must weigh the long-term consequences between choosing a few options; these long term consequences can feel overwhelming, for example, choosing between 2 or 3 different colleges to attend. Therefore, researchers investigating the choice-overload hypothesis should place less emphasis on the number of alternatives presented to users, and more emphasis on the choice-making patterns the situation in the study elicits from the subjects.

The implication for consumer choice researchers is that consumer choice is not simply a function of isolated characteristics of the choice scenario; it is a function of how the various aspects of the choice scenario interact with the consumer’s motives to elicit the choice-making patterns identified in the ASPECT model. Therefore, consumer choice researchers should approach the study of consumer choice, and especially choice overload, not in terms of the outcomes of the choice, but in terms of how the various characteristics of the choice scenario and consumer motives interact to produce specific choice-making patterns (e.g., the attribute based satisficing pattern observed in this study). The best way to achieve this is through a combination of behavioral data and qualitative data as was done in this study (e.g., observing which product pages were viewed most and recording comments from subjects about why they chose the item they did). Once the choice-making pattern that a specific scenario will bring about is understood, then researchers and practitioners may investigate how the isolated characteristics of the scenario can be changed to bias choice (e.g., produce or negate order effects).

5.2 Addressing the Research Questions

Three research questions were the primary drivers of this study: (1) When do recommender systems decrease, rather than increase, consumer choice-making confidence? (2) When do recommender systems increase, rather than decrease, shopping effort? (3) When do recommender systems decrease, rather than increase, satisfaction.

The characteristics of recommender systems examined in this study did not appear to product any strong difference between groups in terms of consumer's confidence, shopping effort, and satisfaction. However, what is clear from the findings is that choice difficulty does have an influence on confidence, effort, and ultimately satisfaction. Considering the issues presented in the discussion above, it would be more prudent to investigate whether and when do recommenders interact with consumer motives and other aspects of the choice situation to elicit the patterns described in the

ASPECT model and which patterns might be associated with outcomes such as effort and confidence.

Recommenders can be designed in a multitude of ways by tweaking the characteristics of recommendation generation and presentation identified in **Table 1-1**. Therefore, it is unlikely that the findings from one study could be generalized to all recommender applications. More fruitful research questions regarding recommender and consumers' experience should ask how the characteristics of recommenders interact with the characteristics of the consumers and choice scenario to produce and bias choice-making patterns. Further, the effects on consumer attitudes, feelings, and perceptions, such as self-confidence, could be investigated.

CHAPTER 6

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

6.1 Conclusion

This study attempted to investigate the general effects of recommender systems on customers' shopping experience. The study of recommender is critical for marketing and information systems researchers. Recommenders are being implemented across many domains, from retail stores to government agencies. These systems represent a general societal trend toward more convenience and efficiency, which can be achieved by recommenders, especially as the number of options and amount of information continues to increase across various choice situations in day-to-day life. Naturally, these systems will continue to become more prevalent. Therefore, understanding how they affect consumers' choice-making patterns is essential for understanding how and why consumers make the choice they do in the coming decades, and even today in many cases.

The choice-overload theory ("the paradox of choice") has remained popular among researchers. In this study, the number of recommendations presented to subjects was manipulated in order to move them to develop greater consideration sets and thus experience greater choice difficulty (choice overload), which would result in negative outcomes in terms of confidence, effort, and satisfaction. These outcomes are important to study because they represent key components of the consumer experience that lead to better relationships and loyalty. In this study, no strong support was found for the influence of an increasing the number of recommendations on confidence, effort, and satisfaction. However, a general choice-making pattern was observed and appeared similar between the three groups. Future studies can investigate how recommender generation and presentation characteristics and influence the choice-making patterns consumers exhibit in particular choice-making scenarios.

6.2 Limitations

This study suffered from several limitations. First, the methodology made it difficult to directly compare website behavioral data with the survey data. It is possible to address this limitations and future studies should do so for a better understanding of how choice-making patterns are impacted by recommenders. As discussed in the previous section, the best approach for understanding choice-making patterns is a combination of behavioral and qualitative data as was done in this study. The results and interpretation would be clearer if the behavioral data could be directly linked to the qualitative responses.

Second, the study was not a real shopping scenario and thus participants had nothing to lose when choosing. An attempt was made to mimic a real retail website as closely as possible as well as to incentivize participants to shop as if they were really purchasing a pen for themselves. However, the effectiveness of the scenario and incentive is not clear. Additional measures should be implemented to help gauge the effectiveness of the study in mimicking a real shopping situation or a field study should be conducted to validate the results.

Lastly, although there was a significant difference in the number of recommendations perceived between groups, in both qualitative (e.g., “few” vs “many”) and quantitative (e.g., “3” or “6”) measures, no difference in the overall perceived assortment size was observed. These results do not necessarily suggest that recommendations cannot alter assortment size perceptions. Other factors, such as the customer motivations when performing the task (e.g., to finish as fast as possible) and other aspects of the recommendation presentation, including presenting an even greater number of recommendations, could still produce an effect on assortment size perception. Moreover, the perceptions of the total number of alternatives may not actually be important. What seems more likely as a determinant of choice difficulty is the size of the consideration set, not assortment size or number of alternatives. Further research on choice overload should be conducted on this basis: how the choice situation and customer motives influence choice-making pattern and thus consideration set.

6.3 Future Work

6.3.1 Pressing Matters

The idea of intelligent agents (which are recommender systems) is often touted as inherently good by both academia and industry. After all, intelligent agents can automate and simplify many tasks as well as provide personalized services to consumers. There are three common arguments for how intelligent agents benefit consumers and businesses. The first is that intelligent agents can help businesses run more efficiently by automating services and replacing human service providers. The second is that intelligent agents can anticipate what consumers want, making suggestions and personalizing offerings without even being prompted. The third is that intelligent agents can help consumers make more intelligent purchasing and lifestyle choices, overcoming the choice and information overload (i.e., distractions) that many today face. However, some scholars argue that intelligent agents can have a “dark side” and are not entirely free of negative outcomes for consumers or businesses.

Bitner (2000) explores how new technologies are changing the nature of services, and in particular, she explores the dark side of technology and service: “technology can assimilate people while at the same time it isolates them; it can provide a sense of control and at the same time feeling of ineptitude; it can facilitate involvement and activity between people while it can simultaneously lead to disconnection and passivity; it can result in greater efficiency and productivity and it can result in wasted time and effort” (pp. 377-378). In addition, not all customers and employees would like to integrate new technologies in their work and personal lives, for many reasons, such as privacy concerns, but all would like to be able to provide and receive high quality service. Moreover, automation and technology infusion in services as a replacement face-to-face human contact can be detrimental to businesses that rely on building relationships with their customers; technology facilitated relationships may not have the same significance.

Information technologies have greatly advanced in the last two decades, but resolutions to Bitner’s concerns do not appear any closer. In fact, if anything, the issues that she has highlighted have been exacerbated. Therefore, one of the most pressing future research issues regarding recommenders and intelligent agents is the need to address the negatives associated with their added efficiency.

Pressing Research Issue 1: Do recommenders overall help make businesses and consumers more efficient in daily tasks, and if so, in what capacity and are there drawbacks or inefficiencies that manifest in other ways?

Kumar (2018) sheds some light on how new technologies are adding to firms' ability to personalize offering and increase efficiency. He argues that marketing is shifting to a new transformative era and that there are several environmental forces that are catalyzing this new era: technology, environmental resources, economic forces, customer preferences, government regulations, and competitive forces. These forces "exert influence on businesses and serve as the instigators for a transformation in the marketing approach" (Kumar 2018, p. 6). An argument could be made that technology itself is the driving force while the others are side effects, but nevertheless, the new environment is pushing companies towards four outcomes: (1) the ability to personalize marketing content, (2) the ability to personalize offerings, (3) higher efficiency, and (4) higher effectiveness (Kumar 2018).

The ability to personalize has come about due to increased volume of data that are available on consumers, new channels in business in daily life, and more sophisticated tracking and real-time interactive software (Kumar 2018). Personalized marketing content can go beyond advertisements and recommendations. Personalization can be used to build relationships and provide customer support through intelligent agents. Personalization of marketing content is has already become the mainstream in digital marketing. Advertising services like Google can even automate the process of creating personalized ads with little input needed from the advertiser. Even now, when using chat support, can you really tell you are speaking with another person?

Personalized marketing goes together with personalized offerings for consumers with lifestyles that are increasingly tending towards heterogeneity and specialized interests (but aren't these specialized wants partly developed because of personalized marketing and recommendations?). Kumar (2018) argues that consumers specialized interests can create inefficiencies in their business. Efficiency increases when more is done with less resources, but customer needs and wants have simply become too diverse for marketers to satisfy them with a one-size-fits-all approach" (Kumar 2018, p.9). Transformative technologies and analytics tools can be used identify areas of inefficiencies and how resources can be better utilized to provide personalized offers. Kumar (2018) provides the example of a tool that advises managers on the budget for their brands based on past performance data. Are recommenders both problem and solution (solving the inefficiencies that they in part create)?

Kumar (2018) states that effectiveness refers "to the medium- to long-term value consequences for all stakeholders involved, realized through the development of better knowledge about customer preferences" (p. 9). This knowledge stems from information gathered about individuals and their preferences which is then used to create competitive advantage (personalized content and offerings) that is delivered via new technologies (recommender systems). According to the transformative view, the current environment naturally pushes companies to strive for these outcomes, but how what is the outcome of perfected personalization on companies and consumers?

Pressing Research Issue 2: How sustainable is it for firms to shift into a process of continual transformation to achieve higher customer personalization? How will striving for perfect personalization affect the stability, culture, and expectations of companies and their customers, and how would these effects feedback into the transformative forces outlined by Kumar2018? What kind of companies could keep up with these efforts? Is the transformative approach appropriate for all firms?

Recommender systems are being implemented by all sorts of firms and institutions to provide an easier choice making experience for users. As their integration continues, like with any other mass-adopted technology, societies can become reliant on recommender systems to the extent that they cannot do without. Recommenders and intelligent agents will become a daily part of every consumer's life, like a shadow or ghost, but one that leads rather than trails behind. But do these systems change consumers themselves?

The word intelligence stems from the Latin words *inter* (meaning between) and *legō* (meaning to choose, pick out, or read); so, from its Latin roots, intelligence literally means the ability to choose between options ("intelligence" n.d.). Recommenders aid in the choosing of options, and as intelligent agents may, in some cases, take over the choice process entirely. How does off-loading choice condition/train the minds of consumers? If at some time in the future (possibly even now?), when recommenders and agents were commonly used for all daily decisions, could they over time affect a person's ability to make choices without assistance? Could recommenders affect a person's intelligence or mental processes in some way, even in their absence?

Jaron Lanier, a computer scientist and virtual reality pioneer, argues that intelligent agents do affect people's intelligence and that the very idea of intelligent agents "is both wrong and evil" (Lanier 1995, p. 66). Lanier (1995) describes the primary argument in favor of intelligent agents: "The idea of agents come up in response to an obvious predicament of the new media revolution we find ourselves hurtling through. How do you make sense of a world of information available to you on demand? How do you find the grains of gold in the heaps of dirt that will be shipped to you on the infobahn everyday? The 'official' answer is that autonomous 'Artificial Intelligence' programs called agents will get to know you by handing out with you and they''' figure it all out, presenting you with a customer morning newspaper, or whatever" (Lanier 1995, p. 66).

Lanier argues that using intelligent agents has significant consequences. First, "if info-consumers see the world through agent's eyes, then advertising will transform into the art of controlling agents, through bribing, hacking…" (Lanier 1995, p. 67). At the time the article was written, such systems were not in place, but they are today, and in fact, with the latest advances in marketing automation across search, email, display advertising, his prediction appear to be coming true; digital marketers are even embracing the "hacker" persona (Shepard 2019). Second, consumers will come to predominantly see the world the agents' eyes, and they will serve as the new information bottle neck. Most importantly, however, are the consequences for human psychology: "agents make people redefine themselves into lesser beings" (Lanier 1995, p.67).

Lanier argues users change themselves in order to make the agent look smart (and themselves look dumb). This occurs through five steps: (1) the person gives the computer program extra deference because it is suppose to be "smart" (which recent research suggest is actually the case (Logg, Minson, and Moore 2019)); (2) the person projects the illusion of autonomy on the computer and begins to think of it like a person; (3) the person then begins to think of themselves like a computer (limiting the idea of human beings to how a computer works); (4) the person beings to limit their ideas to those represented by the program; and (5) when the computer is perceived as an agent, a person will be more willing to adapt their behaviors to "fit naturally into the grooves of the software model… Even without agents, a person's creative output is compromised by identification with a computer. (Lanier 1995, p. 68). In other words, Lanier is suggesting that people adapt themselves to the ideas and capabilities of the technology they use in such a way as to diminish themselves.

Rather than agents, Lanier argues for creating user interfaces and manual editing/filtering tools that empower people to live and work with autonomy in the information age. "Not only must the available tools and techniques strongly influence what work can and will be done, but how it will be done" (Drucker, p. 30). Agents may limit a person's autonomy in their work and personal lives, but perhaps more importantly is how they may condition human psychology to diminish itself. Do intelligent agents really dumb people down?

Therefore, the most prudent research questions for recommender systems research are not concerned with how they relate to business value, but how they can influence and condition consumer's mental processes, specifically consumer's intelligence.

Pressing Research Issue 3: Do recommender systems diminish human autonomy and intelligence?

This last issue has significant implications for education and government. Education is meant to increase intelligence, and therefore autonomy, and the (ideal) purpose of government is to balance autonomy with safety. Recommender systems are becoming more prevalent in both of these domains. For example, technology infusion has persistent and growing from the most elementary to the highest educational institutions, costing taxpayers millions of dollars, but for many schools, the investment has not resulted in any significant improvements in students' intellect.

Will educators and government decision makers become dependent on these systems? What will it mean when those whose responsibility is to preserve intelligence and autonomy cede their responsibility to autonomous systems? More than achieving higher sales, higher personalization, higher efficiency and effectiveness, the most pressing research issue is the impact of recommender systems on intelligence and autonomy.

6.3.2 Potential Future Review Articles

The reviews presented in this dissertation highlight the areas where areas where more integrative reviews are needed to accurately and holistically frame recommender systems within the context of marketing and the greater context of social science. There are at least three review articles needed.

First is an article integrating a typology of societal structures and institutions with recommender systems applications: what domains can recommender systems be integrated into and what are current and potential future real-world examples. Second is an article classifying the algorithmic approaches to recommendation generation and providing of the real-world implementations and outcomes of each. Third is an article identifying the dimensions of recommendation presentation and how presentation affects human decision making in various contexts. Fourth is an article synthesizing the findings of the first three reviews to create a comprehensive typology of recommender systems that would serve as a generator of new research questions and theory for management, marketing, and public policy.

An article comparing the recommender systems with product/information filtering tools would also contribute to the discussion surrounding the issue of technology and autonomy. Filtering tools offer greater control, but recommenders offer greater convenience. Necessarily, filtering tools require the user to exercise their knowledge more than recommenders. Are there any long-term implications for choice making and autonomy when recommenders are more widespread than filtering tools and filtering tools are left underdeveloped? The issues highlighted with automation, efficiency, personalization, autonomy, and intelligence are most pressing and articles addressing the questions raised in this section could steer the future of marketing. The future of technology is the future of marketing.

APPENDIX A

FULL TEXT OF THE SURVEY

The full text of the survey as it was presented to subjects is available below.

Start of Block: Consent Form

Q1.1

The following is a brief summary of the project in which you are asked to participate. Please read this information before signing the statement below. You must be 18 years of age or older to participate in this study.

TITLE OF PROJECT: Online Shopping Experience

PURPOSE OF STUDY/PROJECT: The purpose of this project is to explore how aspects of the website design can affect customer choice.

PROCEDURE: You will complete a shopping task on an e-commerce website that sells pens and then complete the survey on Qualtrics. The survey will ask you about your knowledge of pens, satisfaction, and choice experience. This survey may take approximately 15-20 minutes to complete.

RISKS/ALTERNATIVE TREATMENTS: This research uses surveys and therefore poses minimal risk to participants. If the participant feels any type of risk from answering the questionnaire, they can withdraw the survey at any time without any penalty. Please understand that the researchers are not able to offer financial compensation nor to absorb the costs of medical treatment should you be injured as a result of participating in this research.

BENEFITS/COMPENSATION: You will be able to opt-in to winning the pen you chose on the e-commerce website. To opt-in you must provide your name and physical mailing address when prompted on the Qualtrics survey. You must also remember the name of the pen you chose. If you are selected as a winner the pen you chose will be be shipped to you. Your address must be within the United States to be eligible.

SAFEGUARDS OF PHYSICAL AND EMOTIONAL WELL-BEING: This study involves no treatment or physical contact. All information collected from the survey will be held strictly confidential. No one will be allowed access to the survey other than the researchers.

AGREEMENT: I attest by clicking “Agree” that I have read and understood the following description of the study, “Online Shopping Experience", and its purposes and methods. I understand that my participation in this research is strictly voluntary and my participation or refusal to participate in this study will not affect me in any way. Further, I understand that I may withdraw at any time or refuse to answer any questions without penalty. Upon completion of the study, I understand that the results will be freely available to me upon request. I understand that the results of my survey will be confidential, accessible only to the principal investigators, me, or a legally appointed representative.

I have not been requested to waive nor do I waive any of my rights related to participating in this study. I am 18 years of age or older.

CONTACT INFORMATION: The principal experimenters listed below may be reached to answer questions about the research, subjects' rights, or related matters.

Principal Investigators:

Amin Saleh

mas070@latech.edu

(318) 257-4012

Bruce Alford

balford@latech.edu

(318) 257-3962

Members of the Human Use Committee of Louisiana Tech University may also be contacted if a problem cannot be discussed with principal experimenters:

Dr. Richard Kordal

Director of Intellectual Properties

rkordal@latech.edu

(318) 257-2484

◯ Disagree (1)

◯ Agree (2)

Skip To: End of Block If The following is a brief summary of the project in which you are asked to participate. Please rea... = Disagree

End of Block: Consent Form

Start of Block: Clarification

Q77 This survey is an exercise to determine future website design and is a simulation of purchasing **- you are not actually making a purchase when you click "buy now**." You will visit a website and complete a "purchase" by clicking "buy now" to get an order confirmation code to complete the survey. You are not actually making a purchase and no credit card or financial information will be asked of you. Please read the instructions on the next page carefully to successfully complete the survey.

End of Block: Clarification

Start of Block: Confirmation

Display This Question:

If group = control

Q2.1 **Please read carefully to complete the task or you will not be able to proceed with the survey.**

Imagine that you have received a $25 gift card for the retailer Mastercraft Pens. You decide that you would like to use this gift card now and purchase a nice pen for yourself. Follow the link above by clicking Mastercraft Pens and browse the catalog of pens. Select the pen that is the most appealing to you and return to this page when you have your order confirmation number.

To make a selection, click on the image or text of a pen on the catalog page. You will be take to that pet's product page which contains more information about the pen. Next, click buy now. Then, on the next page, click "Yes" to confirm your choice or "No" to return to the product catalog page if you changed your mind about your selection. You are free to browse as many pens as you like before making a selection.

Once you have clicked "Yes" to confirm your order, you will be taken to the purchase confirmation page. On the purchase confirmation page you will be given an order confirmation number that you must enter below to proceed.

On the next page in this survey you may choose to enter your name and shipping address if you wish to enter the drawing to win your pen of choice. Your address must be within the United States to be eligible. You may also enter your email address if you wish to be notified of winning.

Display This Question:

If group = three

Q2.2 **Please read carefully to complete the task or you will not be able to proceed with the survey.**

Imagine that you have received a $25 gift card for the retailer Mastercraft Pens. You decide that you would like to use this gift card now and purchase a nice pen for yourself. Follow the link above by clicking Mastercraft Pens and browse the catalog of pens. Select the pen that is the most appealing to you and return to this page when you have your order confirmation number.

To make a selection, click on the image or text of a pen on the catalog page. You will be take to that pet's product page which contains more information about the pen as well as recommendations for 3 other pens. Next, click buy now. Then, on the next page, click "Yes" to confirm your choice or "No" to return to the product catalog page if you changed your mind about your selection. You are free to browse as many pens as you like before making a selection.

Once you have clicked "Yes" to confirm your order, you will be taken to the purchase confirmation page. On the purchase confirmation page you will be given an order confirmation number that you must enter below to proceed.

On the next page in this survey, you may choose to enter your name and shipping address if you wish to enter the drawing to win your pen of choice. Your address must be within the United States to be eligible. You may also enter your email address if you wish to be notified of winning.

Display This Question:

If group = six

Q2.3 **Please read carefully to complete the task or you will not be able to proceed with the survey.**

Imagine that you have received a $25 gift card for the retailer Mastercraft Pens. You decide that you would like to use this gift card now and purchase a nice pen for yourself. Follow the link above by clicking Mastercraft Pens and browse the catalog of pens. Select the pen that is the most appealing to you and return to this page when you have your order confirmation number.

To make a selection, click on the image or text of a pen on the catalog page. You will be take to that pet's product page which contains more information about the pen as well as recommendations for 6 other pens. Next, click buy now. Then, on the next page, click

"Yes" to confirm your choice or "No" to return to the product catalog page if you changed your mind about your selection. You are free to browse as many pens as you like before making a selection.

Once you have clicked "Yes" to confirm your order, you will be taken to the purchase confirmation page. On the purchase confirmation page you will be given an order confirmation number that you must enter below to proceed.

On the next page in this survey, you may choose to enter your name and shipping address if you wish to enter the drawing to win your pen of choice. Your address must be within the United States to be eligible. You may also enter your email address if you wish to be notified of winning.

Display This Question:

If group = control

Q2.4 Enter your order confirmation number

____

Display This Question:

If group = three

Q2.5 Enter your order confirmation number

____

Display This Question:

If group = six

Q2.6 Enter your order confirmation number

____

Q2.7 Approximately how many minutes do you believe you spent on the website?

____

Q2.8 Approximately how many product pages do you believe you visited on the website?

____

Q2.9 Which pen did you choose?

____

Q2.10 Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Q78 Browser Meta Info

Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

End of Block: Confirmation

Start of Block: Shipping Information

Q3.1 You may choose to enter your name and shipping address if you wish to enter the drawing to win your pen of choice. Your address must be within the United

States to be eligible. You may also enter your email address if you wish to be notified of winning.

Q3.2 Name (optional)

____

Q3.3 Shipping Address (optional)

____

Q3.4 Email Address (optional)

____

End of Block: Shipping Information

Start of Block: Subjective Product Category Knowledge (Flynn and Goldsmith 1999)

Q4.1 I feel very knowledgeable about pens.

Q4.2 I know how to judge the quality of a pen.

Q4.3 I think I know enough about pens to feel confident when I make a purchase.

Q4.4 I can tell if a pen is worth the price or not.

End of Block: Subjective Product Category Knowledge

Start of Block: Product Involvement

Q5.1 I feel that the products are __________ to me.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
irrelevant	○	○	○	○	○	○	○	relevant
worthless	○	○	○	○	○	○	○	valuable
boring	○	○	○	○	○	○	○	interesting
mundane	○	○	○	○	○	○	○	fascinating

End of Block: Product Involvement

Start of Block: Customer Satisfaction with Website

Q6.1 I enjoyed shopping on this website.

Q6.2 I felt good about the pen I decided to purchase from this website.

Q6.3 This website had a good selection of pens to choose from.

Q6.4 I feel this website provides a good shopping experience.

End of Block: Customer Satisfaction with Website

Start of Block: Online Shopping Convenience

Q7.1 Overall, the website was convenient and easy to use.

End of Block: Online Shopping Convenience

Start of Block: Decision Process Satisfaction

Q8.1 The process of choosing which pen to buy was not frustrating.

Q8.2 I found the process of choosing which pen to buy interesting.

Q8.3 I was satisfied with my experience of choosing a pen.

End of Block: Decision Process Satisfaction

Start of Block: Perceived Decision Effort

Q9.1 I put a lot of effort into making my final choice.

Q9.2 Choosing the right pen took a long time.

Q9.3 It took me a while to find the best option.

End of Block: Perceived Decision Effort

Start of Block: Perceived self-efficacy

Q10.1 I believe I had the ability to choose the product I would be most satisfied with.

Q10.2 I am confident that I was able to choose the product that I would be most satisfied with.

Q10.3 I felt complete control over choosing whichever product I wanted.

Q10.4 The product choice I made was entirely up to me.

End of Block: Perceived self-efficacy

Start of Block: Perceived Decision Freedom

Q11.1 I felt free to choose whichever product I wanted.

Q11.2 I am paying attention to my responses on this survey (please select Strongly Agree or you will be taken out).

Skip To: End of Survey If I am paying attention to my responses on this survey (please select Strongly Agree or you will be... != Strongly agree

End of Block: Perceived Decision Freedom

Start of Block: Choice Confidence

Q12.1 I am satisfied with the pen I chose.

Q12.2 I am confident I selected the pen most suited to my preferences.

Q12.3 I do not wish I could back and change my choice.

End of Block: Choice Confidence

Start of Block: Perceived Decision Quality

Q13.1 I am confident that I made the best possible choice based on my needs.

Q13.2 I am satisfied with the choice I made.

Q13.3 I am certain that I made a good choice.

End of Block: Perceived Decision Quality

Start of Block: Decision Difficulty

Q14.1 Choosing a pen was very difficult for me.

Q14.2 I would need more time to choose a pen.

Q14.3 I felt certain about which pen to choose.

End of Block: Decision Difficulty

Start of Block: Perceived Decision Difficulty

Q15.1 Choosing a pen was difficult.

Q15.2 The task of choosing a pen was complex.

Q15.3 I had difficulty deciding which pen to purchase.

End of Block: Perceived Decision Difficulty

Start of Block: Perceived Information Overload

Q16.1 The amount of information made it difficult to choose a pen.

Q16.2 I did not want to receive more information before making my choice.

Q16.3 I am paying attention to my responses on this survey (please select Strongly Agree or you will be taken out).

Skip To: End of Survey If I am paying attention to my responses on this survey (please select Strongly Agree or you will be... != Strongly agree

End of Block: Perceived Information Overload

Start of Block: Information Overload

Q17.1 There was too much information about the pens.

Q17.2 I was completely flooded by information about the pens.

Q17.3 There was so much information that I was unable to consider it all.

End of Block: Information Overload

Start of Block: Perceived Choice Overload

Q18.1 The number of options made it difficult to choose a pen.

Q18.2 I had trouble choosing a pen due to the number of options.

Q18.3 I felt overwhelmed by the number of options to choose from.

End of Block: Perceived Choice Overload

Start of Block: Perceived Assortment Size

Q19.1 There were many options to choose from.

Q19.2 The number of options to choose from was large.

Q19.3 A large number of options were available to me.

Q19.4 The assortment of pens was plentiful.

End of Block: Perceived Assortment Size

Start of Block: Manipulation Check

Q20.1 After clicking on a pen from the product catalog, how many product recommendations did you see below that pen's description?

○ 0 (0)

○ 3 (3)

○ 6 (6)

Q20.2 After clicking on a pen from the product catalog, there were ______ product recommendations below that pen's description.

○ no (1)

○ few (2)

○ many (3)

Q20.3 Was the pen you chose recommended by the website?

○ No (1)

○ Yes (2)

End of Block: Manipulation Check

Start of Block: Comment Box

Q21.1 Why did you choose the pen you did?

____

Q21.2 Was any part of the shopping task or survey difficult to understand?

____

Q21.3 What would have improved your shopping experience on the website?

____

Q21.4 Feel free to share any additional comments about your experience.

____

Q21.5 What is your sex?

○ Male (1)

○ Female (2)

Q21.6 What is your age?

____

Q75 For mTurk workers: code is 11103

End of Block: Comment Box

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