CONSUMER-BASED INSIGHTS INTO CURATION AND PLATFORM SEARCH

by

JESSICA LYNN BABIN

(Under the Direction of John Hulland)

ABSTRACT

The abundance of online information available to consumers may leave them feeling overwhelmed at the volume of data they must sift through in order to make a choice. I examine two e-commerce domains in which firms can assist in decision-making: curation (i.e., the selecting, organizing, and displaying of content) and platform firms (i.e., online firms that link buyers and sellers). Companies increasingly offer services that curate selections of products for consumers (e.g., the clothing subscription service StitchFix and music playlists on Spotify). Though algorithms drive much of the decision-making behind curation services, companies often choose to present a human curator to consumers. Essay 1 examines the consumer preference for algorithmic over human curators, especially in the context of complex decision-making. Essay 2 focuses on consumer search on online platform firms. I analyze clickstream data to understand the consumer online search process for a complex product and uncover ways the platform firm can assist buyers in making more efficient choices. Finally, in Essay 3, I provide a conceptual framework for understanding the role of curation in marketing. Together, these essays demonstrate that firms can assist consumers in their decision-making, providing value to consumers in a way that also benefits the firm.

INDEX WORDS: Algorithmic decision-making, Humanization, Platform firms, Consumer online search, Clickstream data, Curation, Consumer-based strategy

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DEDICATION

To my parents, Paul and Pam Babin, for your encouragement and unwavering belief in me. I have always felt that I had a safety net in life, allowing me the confidence to attempt my biggest goals. Thank you for your love and support and paying for my cell phone.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

When attempting to make a product or service choice online, today's consumers are faced with an overwhelming landscape of available options, proliferating numbers of online retailers, and seemingly endless reviews and ratings. The abundance of online information available to consumers may leave them feeling overwhelmed at the volume of data they must sift through in order to make a choice. In fact, in 2016, one in five U.S. adults reported feeling "overloaded by information" (Horrigan 2016).

Modern consumers are justified in feeling overwhelmed or overloaded by the amount of information available online. For example, there are enough movies available online that one could spend 47 million years watching them (Tunikova 2018). The music streaming applications Spotify and Apple Music boast giant catalogs of 35 million and 45 million songs, respectively (Savvides and Orellana 2018). There are over 1.8 billion websites, with hundreds more being created by the minute (Tunikova 2018). The abundance of online content extends to products as well; in its eleven country marketplaces worldwide, Amazon lists over three billion products (ScrapeHero 2018).

Given this state of information overwhelm and the increasing number of online shoppers worldwide, I argue that firms have a unique role to play in assisting consumers in their online decision-making. Specifically, my research addresses two online domains in which firms have the opportunity to assist consumers in decision-making: curation (i.e., the selecting, organizing, and displaying of content) and platform firms (i.e., online firms that link buyers and sellers).

This research contributes to the marketing literature on online environments. Within the realm of online firm-consumer interactions, which relates to firms' strategies and tactics in the face of consumers' contact with firms in the online space, much remains to be learned (Yadav and Pavlou 2014). In my three dissertation essays, I show that in a world of digital overload, firms can assist consumers in their decision-making in two understudied areas: curation and platform firms.

Curation

Curation refers to the act of "selecting, organizing, or presenting options (e.g., online content, merchandise, information, etc.), typically with the use of professional or expert knowledge" (Oxford Living Dictionaries 2019). I study two sides of curation: firm and consumer curation. Both firms and consumers have the ability to curate, sifting through what is available amongst the overwhelming amount of online content to find what is worthwhile. Rosenbaum (2014) explains the importance of this role, "The firehose of unfiltered information that's masquerading as content demands a quality curation filter."

"Curation" as a word can be used not only in its original sense (i.e., a specific function at a museum or art gallery), but also in its expanded sense, relating to the selection, arrangement, and display of any type of content. Further, curation as an activity has increased. This can be attributed to the data overload that characterizes today's online world. Given that there is more information available online than any person would be able to sift through in his/her lifetime, consumers must rely on firms and other people to help them uncover what is worthwhile.

Online consumer curation is a relevant activity to marketers, as consumers can curate brand and product images. For example, consumers are actively displaying items they have purchased (e.g., "Every Day Carry" items on the online forum, Reddit), curating items they wish to own (e.g., a collection of images of desired products on the social media platform, Pinterest), and also arranging digital content for the benefit of others (e.g., a themed playlist for a road trip on the music streaming application Spotify).

In order to address the interesting and marketing-relevant activity of online consumer curation, I present a framework to help organize the field's understanding of this process. Online consumer curation is a four-step process - acquiring, selecting, organizing, and displaying content for an audience. There are multiple motivations for consumers to engage in this activity, as well as potential outcomes for the audience that views the curation, all of which I explore in Essay 3 (Chapter 4).

In addition to consumer curation, firms can also act as active curators. Examples of curated services available to consumers include subscription boxes that contain clothing (e.g., Stitch Fix, Trunk Club), lifestyle products (e.g., BarkBox, Loot Crate), and food delivery/meal kits (e.g., NatureBox, Blue Apron). Entertainment streaming is another popular kind of a curated service. Examples include Spotify music creating curated "Discover Weekly" playlists for its users, and Amazon Prime providing curated lists of recommended movies and shows.

One of the most interesting aspects of firm curation is who is framed by the company as doing the decision-making. Some firms present a human as the curator as making the product or content decisions, although an algorithm may actually be responsible. If curation is about adding subjective judgment to a decision or hand-selecting the best content, it may be understandable that firms believe that having a human curator at the helm would be beneficial. Prior research also supports the idea than humanization of products and brands is beneficial to firms. Further, consumers may be hesitant to trust an algorithm to make decisions for them, known as “algorithm aversion.” This tension between algorithmic and human curators in the context of firm curation is a relevant one in the marketplace. Thus, I explore consumer perception and acceptance of algorithm versus human curation in Essay 1 (Chapter 2).

Platform Firms

Platform firms are a more popular business model today than they ever have been before, thanks to the internet. Herrmann (2017) describes platforms as “the underlying trend that ties together popular narratives about technology and the economy in general. Platforms provide the substructure for the ‘gig economy’ and the ‘sharing economy’; they’re the economic engine of social media; they’re the architecture of the ‘attention economy’ and the inspiration for claims about the ‘end of ownership.’” Examples of popular digital platforms include those that serve as retail marketplaces (e.g., Etsy, eBay), and provide services (e.g., Airbnb, Lyft, Kickstarter).

Though the proliferation of this business model on the Internet has brought the attention of the business and popular press, much remains to be studied in the academic literature, especially as platform firms relate to marketing. Within the context of platform firms, I seek to use aggregate consumer search data in order to provide insights to platform firms about what those actions signal regarding continued search or imminent purchase. Thus, my work in Essay 2 (Chapter 3) contributes not only to the platform literature, but also to the growing idea that aggregated consumer search data can be useful in generating insights for the firm.

Abstracts of my three dissertation essays addressing the two main topics of curation and platform firms within the domain of firm-consumer online interactions are listed below.

Essay 1 (Chapter 2)

When Humanization Backfires: Consumer Preference for Algorithmic Product Curation

Companies increasingly offer services that curate the selection of products for consumers (e.g., clothing subscriptions, movie recommendations, music playlists). Though algorithms drive much of the decision-making behind these curation services, companies may choose to humanize their curation services, anticipating that consumers will prefer items selected for them by a human rather than an algorithm. In contrast to the preference for humanization and aversion to algorithms established in the literature, we find that consumers exhibit a preference for algorithmic over human curation across domains including food products, online dating, and entertainment streaming. This preference is driven by the belief that algorithms are superior to humans at managing complex choice option sets, suggesting that consumers may counterintuitively react less positively to humanized curation services. We demonstrate this preference for algorithms across six experiments and an archival dataset of subscription box services. In line with our proposed process, we find that the preference for algorithms is moderated by the perceived complexity of the decision. This research contributes to work that has examined the respective roles of algorithm and humanization on consumer preference, in addition to having practical implications for how firms advertise their product selection process.

Essay 2 (Chapter 3)

Insights for Online Platform Firms from Sequential Consumer Search

Though consumer search and choice have been studied for decades, online data allows new insights into consumers' actual search behaviors. The current research examines consumers' sequential search across multiple sessions for a relatively complex and high-involvement product (i.e., an apartment lease). Using a unique firm-supplied consumer search clickstream dataset, the actions of approximately 8,000 consumers are traceable through their entire search process on the website of a platform firm. Platform firms linking buyers and sellers characterize multisided electronic markets (e.g., eBay, Amazon) and are an important and growing part of online commerce. The main research question investigates whether actions taken by searching consumers can be used to identify an increasing likelihood of purchase by search (web browser) session. Results from multi-level logistic regressions with Bayesian estimation provide evidence that consumer actions in sequential search sessions are differentially important in predicting likelihood over time. This research contributes to an understanding of consumer online search behavior for complex and high-involvement products, as well as providing managerial insights for platform firms.

Essay 3 (Chapter 4)

Curation in Marketing: A Framework

The word "curation" has escaped the art gallery and museum hall to find its way into common vernacular. Examples of online consumer curation include assembling music playlists on Spotify and organizing themed collections of images on Pinterest. As online consumer curators are often using brands and products in their online curation, this activity is of interest to marketers. The actions taken by online consumer curators are similar to those of museum or art gallery curators: acquiring, selecting, organizing, and displaying content for an audience. The motivations for consumers to engage in online curation include building/displaying their identities and making social connections with their online audience. The outcomes possible for the audience that views the curation include gaining access to carefully selected and recommended content. We discuss the possibility for firms to facilitate consumer curation by allowing their product images, for example, to be used as building blocks in consumer curations.

Finally, we suggest several marketing-relevant propositions about this important and understudied area that can be addressed in future research.

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ESSAY 1

WHEN HUMANIZATION BACKFIRES:

CONSUMER PREFERENCE FOR ALGORITHMIC PRODUCT CURATION[1]

[1] A version of this paper is being prepared with coauthors Rosanna K. Smith and John Hulland for submission to *Journal of Consumer Research*.

Abstract

Companies increasingly offer services that curate the selection of products for consumers (e.g., clothing subscriptions, movie recommendations, music playlists). Though algorithms drive much of the decision-making behind these curation services, companies may choose to humanize their curation services, anticipating that consumers will prefer items selected for them by a human rather than an algorithm. In contrast to the preference for humanization and aversion to algorithms established in the literature, we find that consumers exhibit a preference for algorithmic over human curation across domains including food products, online dating, and entertainment streaming. This preference is driven by the belief that algorithms are superior to humans at managing complex choice option sets, suggesting that consumers may counterintuitively react less positively to humanized curation services. We demonstrate this preference for algorithms across six experiments and an archival dataset of subscription box services. In line with our proposed process, we find that the preference for algorithms is moderated by the perceived complexity of the decision. This research contributes to work that has examined the respective roles of algorithm and humanization on consumer preference, in addition to having practical implications for how firms advertise their product selection process.

Companies are increasingly offering curation services to aid consumers' selection of products and services. Curation refers to the act of "selecting, organizing, or presenting options (e.g., online content, merchandise, information, etc.), typically with the use of professional or expert knowledge" (Oxford Living Dictionaries 2019). In the same way that an art curator carefully selects and arranges artwork for a museum exhibit, companies that offer curated services gather and organize options for consumers (Rosenbaum 2011). Examples of curated services available to consumers are plentiful: including clothing subscription boxes (e.g., Stitch Fix, Trunk Club, MM.LaFleur), lifestyle products (e.g., FabFitFun, BarkBox, Loot Crate), and food delivery/meal kits (e.g., NatureBox, Blue Apron, HelloFresh). The market for these e-commerce subscription services has grown more than 100% per year over the past five years; over 15% of online consumers in the United States receive product subscriptions (Columbus 2018). Entertainment streaming is another popular kind of a curated service, with Spotify music creating curated "Discover Weekly" playlists for its users, and Amazon Prime providing curated lists of recommended movies and shows. Indeed, the movie streaming revenue is predicted to outpace global box office revenue in 2019 ($46 billion vs. $40 billion) (Roxborough 2018), and 75% of US music industry revenues came from streaming in the first half of 2018, dwarfing revenue from purchases of physical music (e.g., CDs) and digital downloads (Friedlander and Bass 2018). Moreover, the domain of online dating is projected to reach revenues of $12 billion by 2020 (Rapier 2018).

Algorithms typically drive much of the decision-making behind these curation services (Bhaskar 2016). However, many firms choose to downplay the use of algorithms and instead try to "humanize" the service. For example, Stitch Fix is a clothing subscription company that uses advanced algorithms alongside personal stylists to select fashion items for its customers (Debter

2017). Instead of promoting the use of advanced data science techniques to consumers, the firm emphasizes a human face as the curator responsible for the clothing selection process (e.g., "Try new styles and trends handpicked just for you by a Personal Stylist"). This emphasis on the human side of curation is in line with prior work demonstrating consumer preference for humanized products and services (Schroll, Schnurr, and Grewal 2018; Mourey, Olson, and Yoon 2017; van Doorn et al. 2017), and consistent with the well-established phenomenon of algorithm aversion. Despite the demonstrated superiority of computer assistance in decision-making (Dawes 1979; Dawes, Faust, and Meehl 1989), traditionally individuals have been inclined to distrust computers to make decisions, displaying an aversion to algorithms (Dietvorst, Simmons, and Massey 2014; Yeomans, Shah, Mullainathan, and Kleinberg 2018). However, in this article, we find that consumers actually prefer algorithmic over human decision-making across several consumer-relevant curation domains. We propose that this effect is driven by the consumer belief that people are on average inferior to algorithms at managing complex choice option sets, suggesting that consumers may counterintuitively react negatively to humanized curation services.

This research contributes to a body of work that has explored anthropomorphism and humanization in the context of consumer behavior by establishing a boundary condition of the positive impact of humanization. It also builds on prior work examining individuals' perceptions of algorithmic decision-making by specifically focusing on the processes behind consumer adoption of algorithms designed to select or curate consumer items for the consumer him/herself. The practical implications of the work include suggestions for how firms could advertise their product curation process in order to best attract customers. In light of the growing use of algorithms in consumer contexts, understanding the conditions under which consumers are more or less receptive to knowledge of these processes, and indeed may even react negatively to the humanization of these processes, holds practical relevance for many firms.

In the following sections, we first review prior work that has examined the preference for humans and the aversion to algorithms. Next, we outline our theoretical framework and highlight role of choice complexity in the consumer preference for algorithmic product curation. We then use a mixed methods approach, including six experiments and one regression analysis of an online catalog of subscription boxes (N>2,000), to test our predictions.

Preference for Humanization

Prior work has found that efforts to humanize products or brands can have a positive impact on them (e.g., Aggarwal and McGill 2011; Kim and Kramer 2015). Though there are individual consumer differences in how effective an anthropomorphism strategy is, firms may find that consumers put more trust into the firm (Waytz, Cacioppo, and Epley 2010) and that product evaluations are enhanced (Aggarwal and McGill 2007). Further, humanized brand messengers have been found to be more persuasive (Touré-Tillery and McGill 2015).

In order to reap these positive benefits of humanization, firms often strive to humanize their products and brands (MacInnis and Folkes 2017). One common method by which firms humanize products and brands is by anthropomorphizing them (i.e., giving human-like characteristics to the non-human, Epley, Waytz, and Cacioppo 2007). For example, some firms employ an anthropomorphized spokes-animal (e.g,. Geico’s gecko, Frito-Lay Cheetos’ Chester Cheetah) or add human-like characteristics to inanimate objects or the product itself (e.g., Kellogg’s Frosted Mini-Wheats) in advertising and packaging (Callcott and Phillips 1996). Even when firms do not explicitly attempt to humanize their products or brands, prior work has found that consumers are still likely to seek and find the human in the non-human in many ways.

Consumers may ascribe human characteristics like personalities (e.g., Aaker 1997), form relationships with (e.g., Fournier 1998), and personally identify with products and brands (e.g., Sirgy 1982).

In addition to documenting the positive effect of anthropomorphism on consumer preference, prior work has also examined why consumers hold this preference. Based on long-standing research that humans have the need to belong to and socially connect with other humans (Baumeister and Leary 1995, Maslow 1943), researchers have in turn found that these desires translate to humanized products and brands as well. For example, consumers have been found to prefer handwritten to machine-generated typefaces on products, an effect that researchers attribute to a reconnection to humanness in an automatized and digitized world (Schroll, Schnurr, and Grewal 2018). Further, research has found that interacting with anthropomorphic products can partially fulfill social needs, as social connectedness can be lacking in today's world (Mourey, Olson, and Yoon 2017).

Another reason why consumers may prefer humanized products and brands is that they are able to ascribe positive human traits like warmth and competence to them. In the realm of technological advances, prior work has found that people are more likely to trust new technology and view it as more competent when it is seen as having a more human-like mind (Waytz, Heafner, and Epley 2014). In the same vein, van Doorn et al. (2017) propose that consumers prefer automated service providers (e.g., robots) that display high levels of warmth and competence, traditionally human characteristics. Taken together, this work suggests that people are inclined to look more favorably on humanized products and brands because of our innate desire to connect with other humans.

Aversion to Algorithms in Decision-Making

Not only do consumers prefer humanized products and brands, research has also found that people prefer human decision-makers over the non-human (i.e., technology-enabled decision makers, like algorithms) (Dietvorst, Simmons, and Massey 2014). Research has long found that algorithms beat human predictors at decision-making tasks like making medical diagnoses and predicting student success rates (Dawes 1979; Dawes, Faust, and Meehl 1989), yet people are hesitant to trust them. As a result of a phenomenon known as algorithm aversion, people generally trust decisions made by humans more than those made by algorithms, even when the algorithms are shown to be more accurate. This phenomenon of algorithm aversion has been shown to stem from how quickly people lose confidence in an algorithm after seeing it err; people become less likely to trust the algorithm after seeing it make a mistake, even if that mistake is equal to one made by a human (Dietvorst, Simmons, and Massey 2014).

In addition to algorithms based on predictive models, another important type of algorithmic decision-making is that of recommender systems; thus, some algorithms make objective decisions about the future, while others attempt to make subjective decisions about taste. Recommender systems are those that suggest “other products you may like” on the websites of online retailers, or those that suggest entertainment choices (e.g., movie and music streaming). Comparing algorithms to humans in recommendation contexts, research has found evidence of bias against this type of recommender algorithm as well (e.g., Sinha and Swearingen 2001). Yeomans, Shah, Mullainathan, and Kleinberg (2018) examine the efficacy and acceptance of recommender systems in a subjective context (i.e., predicting how funny a joke is). They find that though the recommender systems objectively outperform humans at selecting jokes, people distrust recommender systems. The effect is driven by the inscrutability of algorithmic recommender systems; people can understand why another human might select the jokes it does but do not understand how algorithms make these decisions. Indeed, when participants were given information about how the algorithmic recommender systems work, their distrust was alleviated (Yeomans, Shah, Mullainathan, and Kleinberg 2018).

Some recent work has begun to explore in what contexts people may be willing to rely on advice from algorithms over advice from other people. Research has found that in the context of quantitative forecasting and estimates, people may be willing to rely on algorithmic advice over advice from humans (Logg, Minson, and Moore 2018). When tasked with making a numeric judgment (e.g., guessing someone's weight, predicting a song's success on the charts), people were more willing to rely on algorithmic advice than on advice from another person. Researchers suggest that consumers may feel more comfortable with algorithmic advice in predicting in objective domains like forecasting future events (e.g., sports winning predictions). Importantly, forecasting expertise had a moderating effect; they find that experts are more likely to discount advice from both humans and algorithms (Logg, Minson, and Moore 2018). We build on these findings by examining when consumers might choose an algorithmic recommender system over a human to make a decision for them, even without being given an explanation of how the algorithm works.

Human Versus Algorithm in the Context of Firm Curation

In this paper, we focus specifically on how consumers respond to human versus algorithmic decision-making in the context of firm curation. Curated services are those that select, organize, and display content like products (e.g., subscription boxes) or entertainment/media (e.g., Pandora or Spotify music streaming) for consumers. The selection of items (i.e., curating) can be done by either human curator or, with the advent of increasingly sophisticated data science techniques, an algorithmic curator. Drawing together the work on anthropomorphism and algorithm aversion, one might predict a strong consumer preference for decisions made by a human rather than an algorithm. Framing a product or service as being chosen by a human should be more preferred by consumers. However, drawing from work examining the role of complex choice sets in consumption, we predict that in the context of curated consumer products and services, consumers exhibit not only a lack of preference for a human but also a preference for products and services curated by an algorithm.

We predict that consumers will prefer an algorithmic curator over a human one due to consumers' knowledge of human limitations. For example, in the face of complex decisions, humans can face choice overload. "Choice overload" describes when an individual's cognitive resources are exceeded by the level of decision complexity (Simon 1955, Toffler 1970). Choice overload may lead to consumers delaying or rejecting a choice, a negative subjective state (e.g., decision regret) or a behavioral outcome (e.g., likelihood of switching). We draw on the literature on choice overload which has shown that consumers can be overwhelmed in the face of complex decisions, including those stemming from large assortment sizes (Chernev, Böckenholt, and Goodman 2015). It has been found that not only does increasing the number of products available to consumers not increase their satisfaction level with their choice (Reibstein, Youngblood, and Fromkin 1975), but in fact may decrease their satisfaction with their choice (Iyengar and Lepper 2000; Diehl and Poyner 2010).

Despite issues of choice overload and the evidence that having more options may decrease satisfaction, there are obvious benefits to large assortments as well. Classic research shows that consumers are more likely to find a superior option, given their purchase goals, from a larger choice set (Baumol and Ide 1956, Hotelling 1929). Further, large assortments, which give consumers more available options from which to choose can lead to a more enjoyable shopping experience (Babin, Darden, and Griffin 1994), and can make them feel more satisfied with their purchase choice (Botti and Iyengar 2004). Retailers may even choose to organize their offerings into categories, which increases perception of variety, leading to greater consumer satisfaction (Mogilner, Rudnick, and Iyengar 2008). Some research has argued that increasing assortment size is always beneficial for the retailer, as adding items to a choice set increased the consumer's evaluation of that assortment (Oppewal and Koelemeijer 2005).

Algorithmic curation allows the consumer to have the best of both worlds: a choice from a large assortment of options, without the threat of choice overload, for either the consumer his/herself or the human curator. In this research, we predict that choice complexity moderates the effect of consumer preference for algorithmic decision-making in the context of curated consumer products/services. We propose that consumers, when faced with selecting a human or an algorithm to sort through a large number of options on their behalf, will trust the algorithm to better handle the task. The consumers will recognize the possibility for the human to experience choice overload and thus believe the algorithm to be better equipped to curate for them. We propose that in the face of decision complexity, consumers will be more likely to want to try a curated service with items (e.g., music, products) chosen by an algorithm than a human.

Overview of Studies

Six experiments and one archival study examined the preference for human versus algorithmic decision-making in the curation of consumer products and services. Study 1 tested our basic effect: whether consumers prefer an algorithm or a human decision-maker in consumer curation context (i.e., packaged goods). Study 2 then tested the preference in a different domain and our proposed process—that algorithms are preferred to humans because they are seen as more competent at managing complex choice sets—via a mediation approach. Study 3 then tested this proposed process via a moderation approach by directly manipulating choice set complexity. Studies 4A and 4B explored two types of complex decisions: quantitatively-complex (large assortments) and qualitatively-complex decisions (complex in non-quantifiable ways). Study 5 tested the extent to which relative trust for algorithms versus humans plays a role in the preference. Finally, Study 6 tested the preference for algorithms in an archival study of an online catalog of subscription boxes (N>2,000), revealing evidence from the marketplace of the impact of humanizing a curated service.

Study 1: Revealed Preference for Algorithm vs. Human Curation

Study 1 provides an initial test of whether consumers prefer algorithmic or human decision-making in the curated selection of consumer products for them. Participants viewed a hypothetical snack subscription box with a monthly selection of food products curated by either an algorithm or an expert food blogger (human). The images in the stimuli reflected the curator behind the product selection: a stream of computer code for the algorithm condition, and a hand holding snacks, in order to emphasize the computer or human curator, respectively. The algorithm and anthropomorphism literature would predict a strong consumer preference for the human-curated service over the algorithm-curated option. This study provides a baseline test of whether consumers will prefer a human or an algorithm to curate for them.

Methods

We recruited 187 participants from Amazon's Mechanical Turk, eliminating 26 for failing an attention check, leaving a total of 161 study subjects (M_{age} = 35.9; 54.7% male). In a between-subjects design, participants were randomly assigned to the algorithm or human condition. In both conditions, they learned about a snack subscription box service, SnackBox.

Participants in the algorithm condition viewed an image of the curation process (see Figure 2.1, image on left) with a description that specified that the products were selected using an algorithm:

> *SnackBox delivers you a curated selection of high-quality and delicious snacks. The snacks are computer-selected by an Advanced Algorithm, which selects each month's snacks based on customers' feedback.*

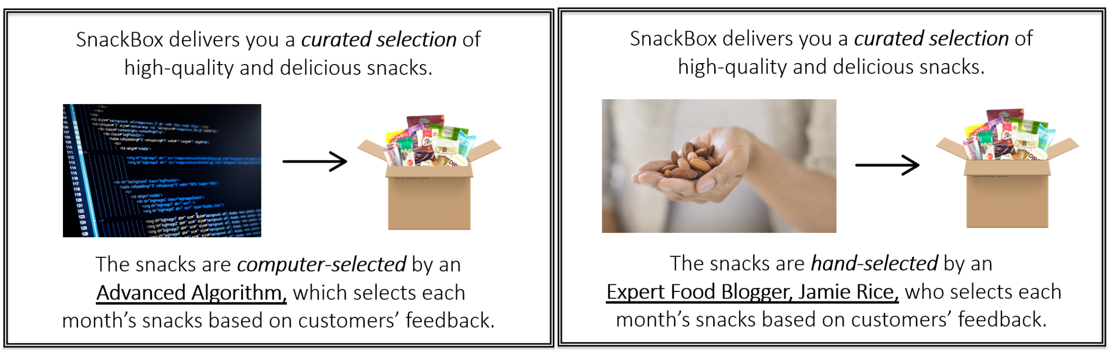

FIGURE 2.1

ALGORITHM VS. HUMAN CURATION STIMULI FOR STUDY 1

Those in the human condition viewed an analogous image of the selection process (see Figure 2.1, image on right) but with the specification that the products were selected by an expert food blogger:

> *SnackBox delivers you a curated selection of high-quality and delicious snacks. The snacks are hand-selected by an Expert Food Blogger, Jamie Rice, who selects each month's snacks based on customers' feedback.*

After viewing the descriptions, participants in both conditions rated the subscription box on the following three-item willingness to try subscription service scale: How likely are you to try out this service? (1 = *Not at all likely*, 7 = *Very likely*); How likely are you to try SnackBox? (1 = *Not at all likely*, 7 = *Very likely*); How much would you like to try out the SnackBox service? (1 = *Not at all*, 7 = *Very much*). Responses to these items were highly correlated (α = .94) and were averaged to create a single composite measure of willingness to try the subscription service.

Results and Discussion

Results revealed that participants were significantly more willing to try the subscription service when the items were chosen by an algorithm ($M_{\text{algorithm}} = 4.15$, $SD = 1.62$) than by a human ($M_{\text{human}} = 3.27$, $SD = 1.73$, $t(159) = 3.43$, p =.001, d = .47).

These results provide initial evidence that consumers are not only willing to accept a service (e.g., a subscription box) with items selected by an algorithm, but actually prefer it to the same product service selected by a human. These results are curious in light of prior work that has found that consumers prefer humanized products and services (e.g., Mourey, Olson, and Yoon 2017; Schroll, Schnurr, and Grewal 2018). This raises the question of *when* consumers would reject humans in favor of algorithms, seemingly in contrast to the established literature. We propose that in the case of complex decision tasks, consumers may prefer to let an algorithm make decisions for them, believing that the algorithm will be more competent than a human. Next, Study 2 tested this proposed mechanism that the perception of the decision maker's competence at handling complexity drives the preference for algorithmic over human decision-making.

Study 2: Mediation by Curator Capability

The main question that arose from the previous study is *why* consumers would prefer to have an algorithm rather than a human expert select items for them. We propose that consumers are operating with the assumption that algorithms are more capable than humans at selecting things for them in complex decision scenarios. Curating services are inherently about sifting through lots of options, a complex task, in order to choose items on behalf of the consumer. Thus, competence is an important aspect in choosing to outsource decision-making to another entity, either a person or an algorithm, especially in a complex task scenario. We propose that the perceived competence of the decision maker mediates the main effect, preference for an algorithm-curated service, found in Study 1. Study 2 tested this proposed driver of the preference for algorithmic over human decision-making - participants must decide whether a human or an algorithm would be preferred to make decisions for them, as well as how competent at that task the decision-maker would be.

Methods

We recruited 200 participants from Amazon's Mechanical Turk, eliminating 16 for failing an attention check, leaving a total of 184 study subjects ($M_{age} = 38.0$; 47.8% male). In a between-subjects design, participants were randomly assigned to the algorithm or human condition. In both conditions, they learned about a music streaming application, MusicStream. First, they read: "Imagine that you are in the market for a music streaming application for your phone/computer and that the service is priced reasonably." Participants in the algorithm condition then viewed an image of the curation process (see Figure 2.2, image on left) with a description that specified that the playlists were selected using an algorithm:

> *MusicStream delivers you curated playlists of music you'll love! How the MusicStream Service Works: 1. Listen to your favorite music on your device of choice 2. Your information will be analyzed by our Advanced Algorithm 3. The Advanced Algorithm chooses songs from a database 4. Receive personalized playlists selected by our Advanced Algorithm*

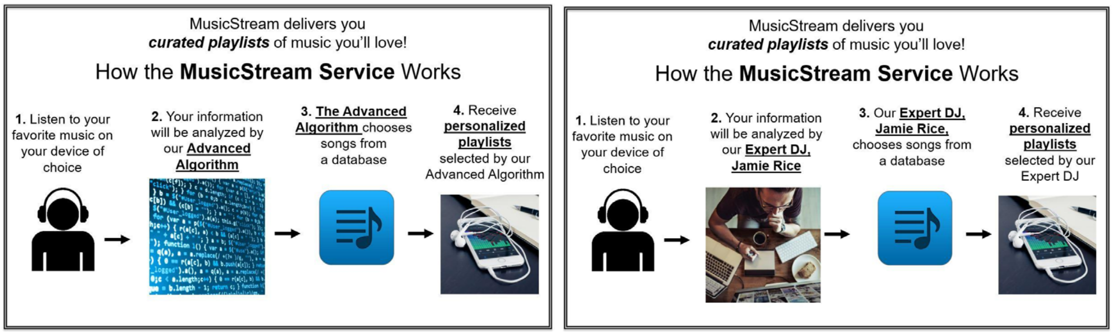

FIGURE 2.2

ALGORITHM VS. HUMAN CURATION STIMULI FOR STUDY 2

Those in the human condition viewed an analogous image of the selection process (see Figure 2.2, image on right) but with the specification that the playlists were selected by an expert DJ:

1. Listen to your favorite music on your device of choice 2. Your information will be analyzed by our Expert DJ, Jamie Rice 3. Our Expert DJ, Jamie Rice, chooses songs from a database 4. Receive personalized playlists selected by our Expert DJ

We measured perceptions of the participants' willingness to try the service using the same three-item scale used in Study 1. Responses to these items were highly correlated (α = .98) and were averaged to create a single composite measure of willingness to try subscription service.

We also measured perceptions of the curator's capability at making a choice from among many options using the following three items: I think that this Advanced Algorithm (Expert DJ) would be good at selecting across a lot of options. (1 = *Strongly disagree*, 7 = *Strongly agree*); I think that this Advanced Algorithm (Expert DJ) could handle selecting from a large database of song options. (1 = *Strongly disagree*, 7 = *Strongly agree*); I believe that this Advanced Algorithm (Expert DJ) would be good at making choices from among many options. (1 =

Strongly disagree, 7 = *Strongly agree*). Responses to these items were highly correlated ($\alpha = .95$) and were averaged to create a single composite measure of curator capability.

Results and Discussion

The main effect of preference for an algorithm as a curator of a service over a human was replicated: participants were much more willing to try the service curated by an algorithm ($M_{\text{algorithm}} = 4.64$, $SD = 1.67$) than by a human ($M_{\text{human}} = 3.69$, $SD = 2.13$, $t(182) = 3.40$, $p = .001$, $d = .49$). Additionally, participants in the algorithm condition attributed significantly more capability at choosing from a large assortment to the algorithm curator ($M_{\text{algorithm}} = 5.15$, $SD = 1.45$) compared to those in the human curator condition ($M_{\text{human}} = 4.26$, $SD = 1.80$, $t(182) = 3.69$, $p < .001$, $d = .54$).

We predicted that curator capability (i.e., ability to handle making a choice in a complex condition) would mediate the effect of the curator (algorithm or human) on behavioral intentions (willingness to try the subscription service). We conducted a bootstrapping analysis (Hayes 2013) with algorithm/human condition as the independent variable and willingness to try subscription service as the dependent variable. This analysis (10,000 resamples) revealed that curator capability significantly mediated the relationship (indirect effect = .74, SE = .21, 95% CI = [.34, 1.15]). Specifically, we found that an algorithmic curator increased perceived competence at handling complexity ($a = .88$, $p < .001$), which then increased participants' willingness to try the service ($b = .84$, $p < .001$). Including curator's competence with complexity in the model made the relationship between the curator (algorithm / human) and willingness to try the service non-significant ($c' = .21$, $p = .30$), reflecting full mediation.

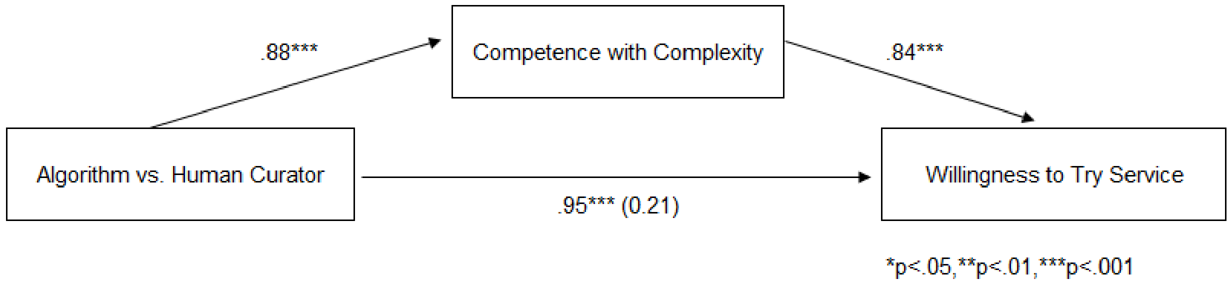

FIGURE 2.3

MEDIATION ANALYSIS FOR STUDY 2

Study 3: Moderation By Complexity of Decision Task

The previous study measured participants' perceptions of the competence of the curator and found that it mediated the relationship between the curator and the participants' willingness to try the service. In Study 3, we tested our proposed process via a moderation approach by directly manipulating the level of complexity of the decision task. Specifically, we theorize that an algorithm will be preferred in situations that reflect a high level of choice complexity, due to the perceived competence of algorithms. Choices can be viewed as complex due to many different factors; in this study, we operationalize decision task complex by the assortment size from which products (here, songs in a music streaming application) are chosen.

We propose that participants will recognize the limitations of a human's, even an expert's, ability to make decisions in very complex scenarios. Likely, the participants will believe that they themselves would be seized by "choice overload" in the high complexity condition and project that feeling onto the human curator. Thus an algorithm-curated service would be preferred, given the perceived competence of algorithms at handling complex decisions, including those that stem from large assortments. Study 3 tested this proposed moderator of the preference for algorithmic over human decision-making - as the participants are faced with a scenario that seems very complex, they must decide whether a human or an algorithm would be preferred to make decisions for them.

Methods

We recruited 365 participants from Amazon's Mechanical Turk and removed 62 participants for failing the attention check, leaving a total of 303 participants (M_{age} = 38.4; 49.5% male). In a 2(curator: algorithm vs. human) x 2(complexity of decision task: high vs. low) between-subjects design, participants viewed information about MusicStream, a music streaming service with playlists either selected by an Advanced Algorithm or an Expert DJ and either chosen from a database of 500 (low complexity) or 5,000,000 (high complexity) songs. First, all participants read the following: *Imagine that you are in the market for a music streaming application for your phone/computer and that the service is priced reasonably.*

Participants in the algorithm x low complexity condition viewed an image of the selection process (see Figure 2.3, image on top left) with this description:

> *MusicStream delivers you curated playlists of music you'll love! How the MusicStream Service Works: 1. Listen to you favorite music on your device of choice 2. Your information will be analyzed by our Advanced Algorithm 3. The Advanced Algorithm chooses songs from a database of 500 songs 4. Receive personalized playlists selected by our Advanced Algorithm.*

Participants in the algorithm by high complexity condition viewed the same image and description of the selection process (see Figure 2.3, image on top right), but with a change to the database from which the songs are selected: *3. The Advanced Algorithm chooses songs from a database of 5,000,000 songs.*

Participants in the human by low complexity condition viewed an image of the selection process (see Figure 2.3, image on bottom left) with this description:

MusicStream delivers you curated playlists of music you'll love! How the MusicStream Service Works: 1. Listen to you favorite music on your device of choice 2. Your information will be analyzed by our Expert DJ, Jamie Rice 3. Our Expert DJ, Jamie Rice, chooses songs from a database of 500 songs 4. Receive personalized playlists selected by our Expert DJ.

Participants in the human x high complexity condition viewed the same image and description of the selection process (see Figure 2.3, image on bottom right), but with a change to the database from which the songs are selected: *3. Our Expert DJ, Jamie Rice, chooses songs from a database of 5,000,000 songs.*

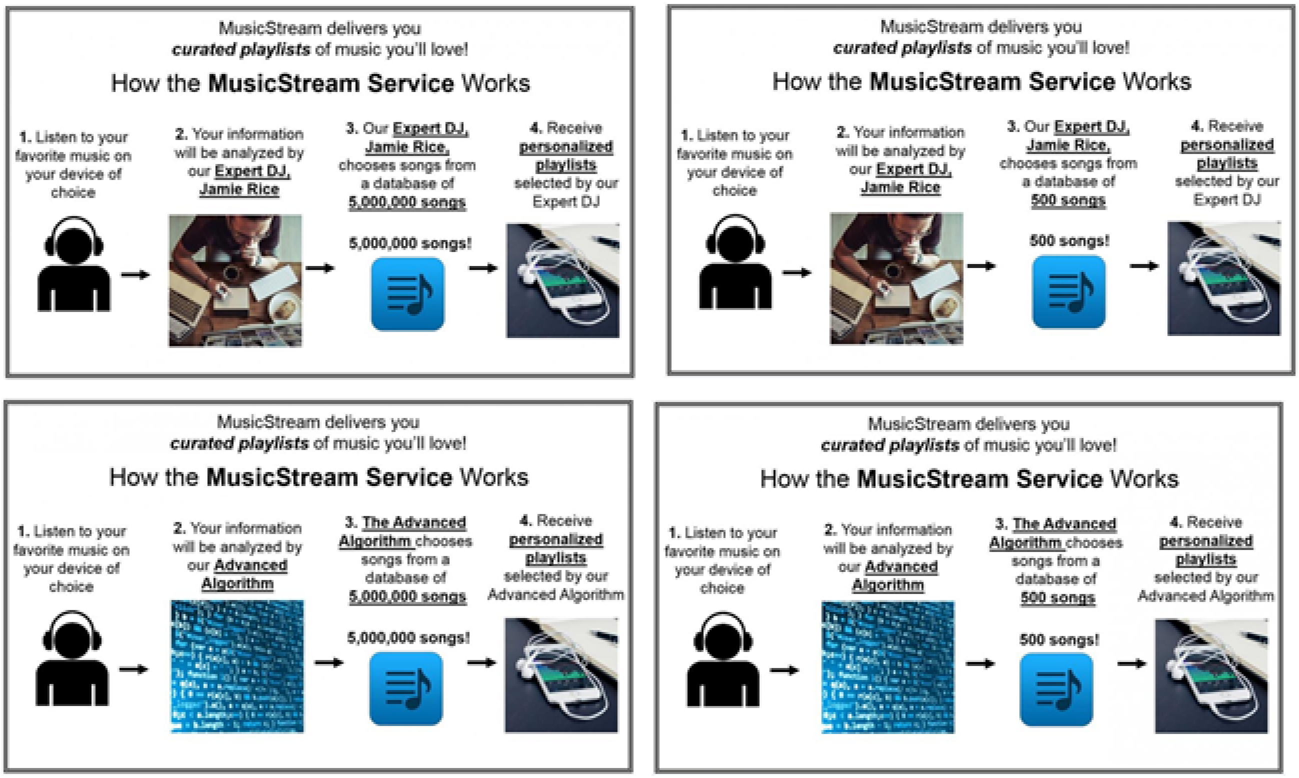

FIGURE 2.4

2 x 2: ALGORITHM VS. HUMAN DECISION MAKER AND

LOW VS. HIGH COMPLEXITY FOR STUDY 3

We then measured perceptions of the participants' willingness to try the service using the same three-item scale used in Study 1. Responses to these items were highly correlated ($\alpha = .98$) and were averaged to create a single composite measure of willingness to try subscription service.

Results and Discussion

A 2(curator: algorithm vs. human) x 2(complexity of decision task: high vs. low) between-subjects ANOVA revealed a marginally significant two-way interaction of decision maker and complexity, $F(1, 302) = 3.68$, $p = .056$. There was also a marginally significant main effect of decision maker, $F(1, 302) = 2.83$, $p = .094$, and a significant main effect of complexity $F(1, 302) = 14.32$, $p < .001$. Simple slopes revealed that, when the decision was complex, consumers preferred the algorithm ($M_{\text{algorithm}} = 4.68$, $SD = 1.71$) over the human ($M_{\text{human}} = 3.89$, $SD = 1.95$; $t(164) = 2.78$, $p = .006$, $d = .43$). In contrast, when the decision complexity was low, there was no difference in preference between algorithm ($M_{\text{algorithm}} = 3.43$, $SD = 1.89$) and human ($M_{\text{human}} = 3.48$, $SD = 2.05$; $t(135) = -0.15$, $p = .88$, $d = .03$; see Figure 2.5. Thus, when the curator is framed as making a very complex decision, an algorithm was the preferred decision maker.

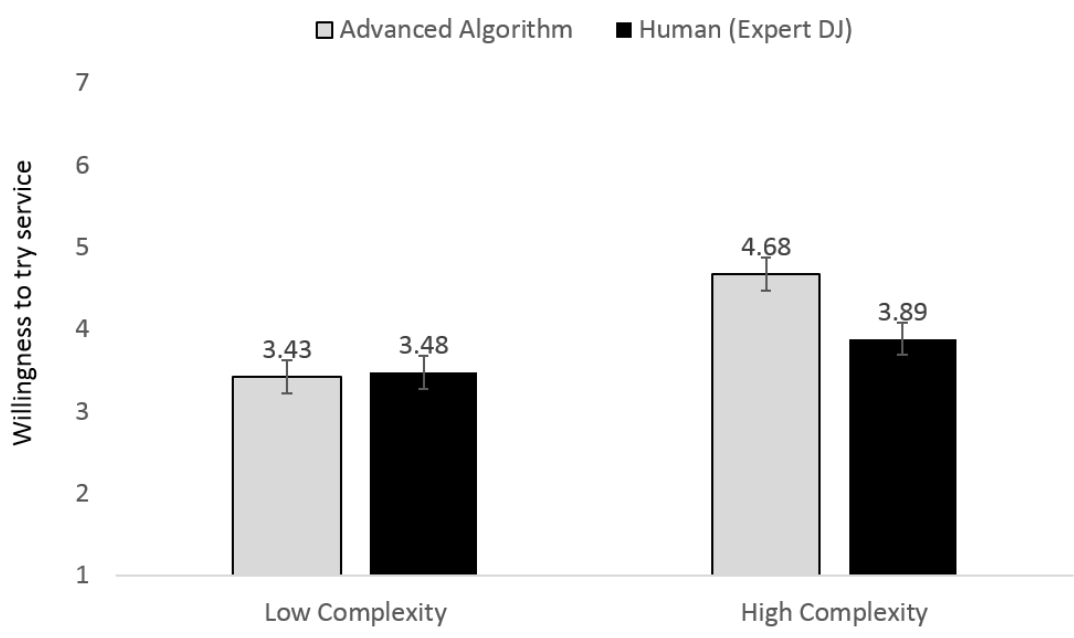

FIGURE 2.5

WILLINGNESS TO TRY SERVICE BY CURATOR AND COMPLEXITY OF DECISION TASK FOR STUDY 3

When participants are faced with outsourcing a decision in a high complexity scenario like music streaming (choosing songs from a large assortment), the main effect of preference for a service curated by an algorithm holds. Participants trust an algorithm to be able to make good decisions in a high complexity condition, effectively able to choose from among a very large assortment. In Study 3, high and low complexity were operationalized by assortment size, a type of quantitative complexity. The next two studies examine whether type of complexity, quantitative or qualitative, has an impact on the main effect of preference for algorithm.

Study 4A: Moderation by Type of Complexity of Decision Task

Study 4A examines whether the main effect of preference for algorithm over human holds in not only in a quantitatively-complex setting (e.g., choosing amongst a large assortment size), but also a qualitatively-complex condition. Qualitatively-complex conditions are those that are complicated not due to a quantifiable metric (e.g., number of options available), but rather an aspect that is more qualitative in nature. In Study 4A, we examine the context of a movie streaming application. In this situation, curating movies could be a quantitatively complex task (e.g., choosing from amongst millions of options, akin to Netflix recommender algorithms) or a qualitatively complex task (e.g., using critical judgment to select quality films).

Method

We recruited 367 participants from Amazon's Mechanical Turk and removed 56 participants for failing the attention check, leaving a total of 311 MTurk participants (M_{age} = 36.4; 49.2% male). In a 2(curator: algorithm vs. human) x 2(type of complexity of decision task: quantitative vs. qualitative)** between-subjects design, participants viewed information about MovieStream, an online movie streaming service with a curated selection of films either selected by an Advanced Algorithm or an Expert Film Critic and featuring either a quantitatively or qualitatively-complex decision. The quantitatively-complex condition offered movies chosen from a huge database of 5,000,000 movies, while the qualitatively-complex condition considered the creativity, originality, and uniqueness of movies. First, all participants read the following:

Imagine that you are in the market for a movie streaming application for your phone/computer and that the service is priced reasonably.

Participants in the algorithm x quantitatively-complex condition viewed an image of the selection process (see Figure 2.6, image on top left) with this description:

> *How the MovieStream Service Works 1. Watch your favorite movies on your device of choice 2. Your information will be analyzed by our Advanced Algorithm 3. Our Advanced Algorithm chooses movies from a huge database of 5,000,000 movies 4. Receive a curated selection of movies you'll love, chosen for you by our Advanced Algorithm.*

Participants in the algorithm x qualitatively-complex condition viewed the same image and description of the selection process (see Figure 2.6 image on top right), but with a change to Step 3: *Our Advanced Algorithm considers the creativity, originality, and uniqueness of movies in order to choose cinematic gems.*

Participants in the human x quantitatively-complex condition viewed an image of the selection process (see Figure 2.6, image on bottom left) with this description:

> *1. Watch your favorite movies on your device of choice 2. Your information will be analyzed by our Expert Film Critic, Jamie Rice 3. Our Expert Film Critic chooses movies from a huge database of 5,000,000 movies 4. Receive a curated selection of movies you'll love, chosen for you by our Expert Film Critic.*

Participants in the human x qualitatively-complex condition viewed the same image and description of the selection process (see Figure 2.6, image on bottom right), but with a change to Step 3: *Our Expert Film Critic considers the creativity, originality, and uniqueness of movies in order to choose cinematic gems.*

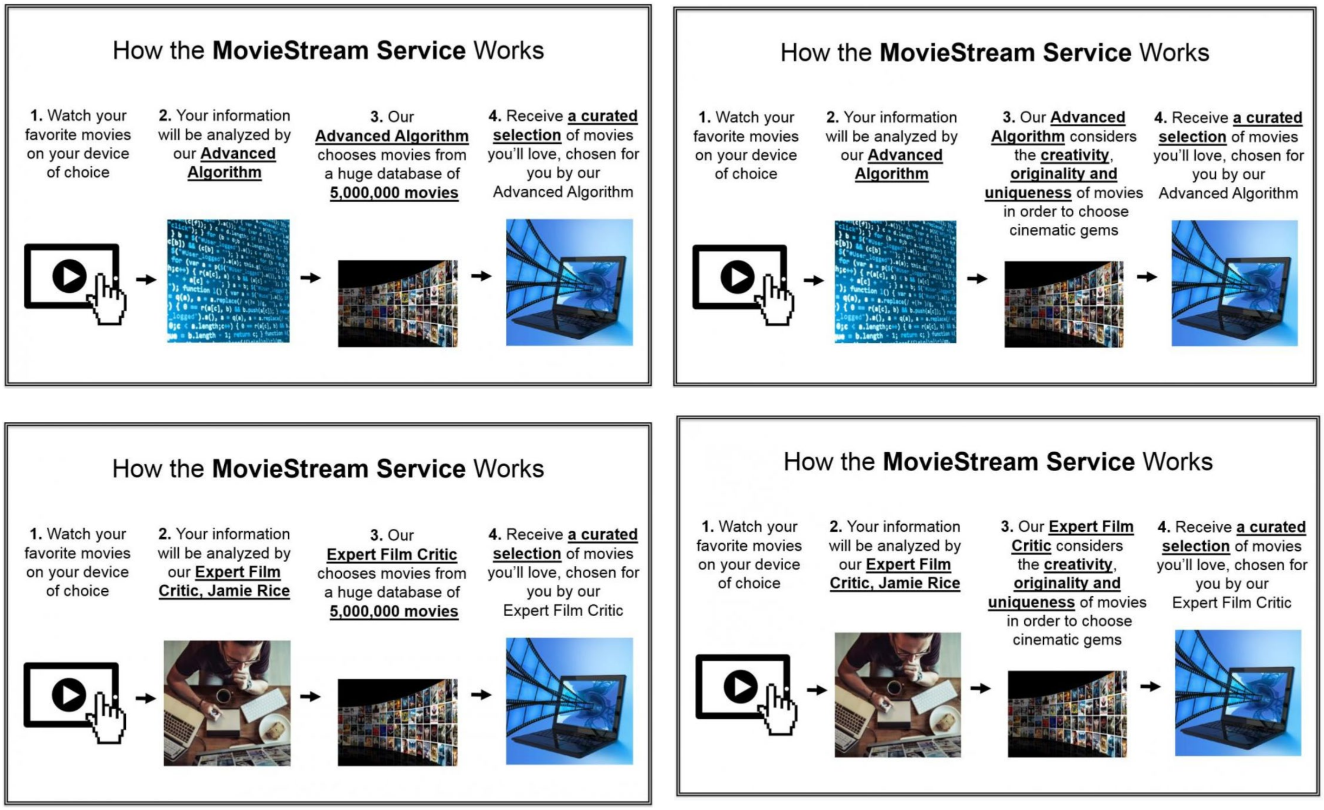

FIGURE 2.6

2 x 2: ALGORITHM VS. HUMAN DECISION MAKER AND QUANTITATIVELY VS. QUALITATIVELY COMPLEX TASK FOR STUDY 4A

We then measured perceptions of the participants' willingness to try the service using the same three-item scale used previously: How likely are you to try out this service? (1 = *Not at all likely*, 7 = *Very likely*); How much would you like to try out the MovieStream service? (1 = *Not at all*, 7 = *Very much*); How likely are you to try MovieStream? (1 = *Not at all likely*, 7 = *Very likely*). Responses to these items were highly correlated (α = .98) and were averaged to create a single composite measure of willingness to try subscription service.

Results and Discussion

A 2(curator: algorithm vs. human) x 2(type of complexity of decision task: quantitative vs. qualitative)[2] between-subjects ANOVA revealed a significant main effect of decision maker, $F(1, 310) = 9.04$, $p = .003$, but no significant main effect of complexity $F(1, 310) = 0.12$, $p = .726$ and no significant effect of the two-way interaction of decision maker and type of complexity, $F(1, 310) = 0.73$, $p = .392$. Simple slopes revealed that, when the decision was qualitatively complex, consumers preferred the algorithm ($M_{\text{algorithm}} = 4.64$, $SD = 1.60$) over the human ($M_{\text{human}} = 3.86$, $SD = 1.86$; $t(141) = 2.67$, $p = .008$, $d = .45$). Similarly, when the decision was quantitatively complex, there was a marginally significant difference in the preference for the algorithm ($M_{\text{algorithm}} = 4.54$, $SD = 1.73$) over the human ($M_{\text{human}} = 4.10$, $SD = 1.83$; $t(166) = 1.56$, $p = .120$, $d = .25$). So, when presented with either a qualitatively or quantitatively-complex decision, the preference for algorithm over human decision maker holds.

[2] The qualitative and quantitative conditions were pretested and were perceived to be significantly qualitatively (M = 5.00, SD = 1.39; t(99) = 7.18, p < .000) and quantitatively complex (M = 4.40, SD = 1.92; t(101) = 2.11, p = .037), respectively.

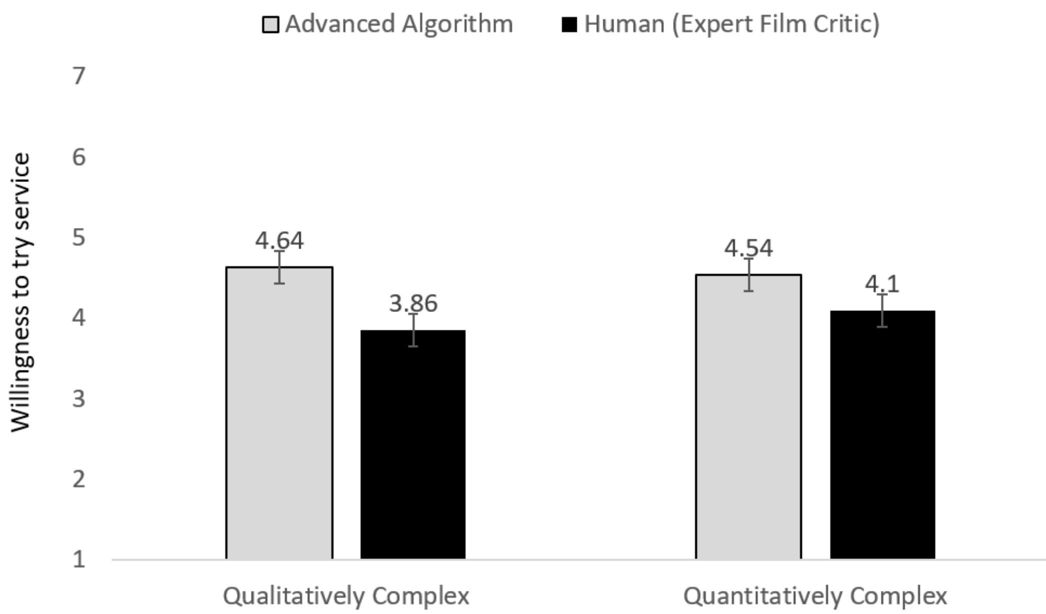

FIGURE 2.7

2 x 2: WILLINGNESS TO TRY SERVICE BY CURATOR (ALGORITHM OR HUMAN) AND TYPE OF COMPLEXITY OF DECISION TASK FOR STUDY 4A

It is perhaps not surprising that an algorithm might be more effectively able to handle decision-making under a quantitatively complex condition than a human. However, it is quite surprising that an algorithm would also be the preferred decision maker under a qualitatively complex condition, in which human judgment might have be seen to be necessary. Participants' preference for the algorithmic decision maker seems to hold in all complex scenarios, despite the type of complexity.

Study 4B: Moderation by Type of Complexity of Decision Task

Study 4B further examined whether the type of complexity, quantitative vs. qualitative, has an impact on the preference for algorithmic over human decision-making. Here, the participants' preference is evaluated in a highly subjective domain, an online dating service. We specifically chose this context, as evaluating other humans as potential relationship matches is a task that might be seen as especially qualitative, and thus better undertaken by humans. In fact, research has shown that potential matches in an online dating context are "goods defined by attributes that are subjective, aesthetic, holistic, emotive, and ties to the production of sensation" (Frost, Chance, Norton, and Ariely 2008, p.52). This study demonstrates again the consumer preference for algorithmic over human decision making, even in a context (making judgments about potential matches) in which human judgment might be perceived as useful.

Methods

We recruited 399 MTurk participants from Amazon's Mechanical Turk and removed 107 participants for failing the attention check, leaving a total of 292 MTurk participants (M_{age} = 36.0; 50.3% male). In a 2(curator: algorithm vs. human) x 2(type of complexity of decision task: quantitative vs. qualitative) between-subjects design, participants viewed information about MatchUp, an online dating service that provides a curated selection of possible matches, either selected by an Advanced Algorithm or an Expert Matchmaker and featuring either a quantitatively or qualitatively-complex decision. The quantitatively-complex condition offered scientifically-optimal matches selected from a database of 150,000, while the qualitatively-complex condition provided matches based on "who you truly are as a person." First, all participants read the following: *Imagine that you are in the market for an online dating service and that the service is priced reasonably.*

Participants in the algorithm x quantitatively-complex condition viewed an image of the selection process (see Figure 2.8, image on top left) with this description:

How the MatchUp Service Works: Fill out a survey and enter into a pool of 150,000 others who have filled out the same survey; Our Advanced Algorithm analyzes the *information collected from 150,000 people, ultimately leading to scientifically optimal matches; Receive a curated selection of potential matches, chosen for you by our Advanced Algorithm.*

Participants in the algorithm x qualitatively-complex condition viewed a parallel description of the selection process (see Figure 2.8 image on top right), with the following text:

How the MatchUp Service Works: Express your personality, values, and desires in a recorded conversation with our Advanced Algorithm; Our Advanced Algorithm reflects on your conversations about who you truly are as a person, ultimately leading to matches that are based on your true self; Receive a curated selection of potential matches, chosen for you by our Advanced Algorithm.

Participants in the human x quantitatively-complex condition viewed an image of the selection process (see Figure 2.8, image on bottom left) with this description:

How the MatchUp Service Works: Fill out a survey and enter into a pool of 150,000 others who have filled out the same survey; Our Expert Matchmaker, Jamie Rice, analyzes the information collected from 150,000 people, ultimately leading to scientifically optimal matches; Receive a curated selection of potential matches, chosen for you by our Expert Matchmaker.

Participants in the human x qualitatively-complex condition viewed a parallel description of the selection process (see Figure 2.8 image on bottom right), with the following text:

How the MatchUp Service Works: Express your personality, values, and desires in a recorded conversation with our Expert Matchmaker; Our Expert Matchmaker, Jamie Rice, reflects on your conversations about who you truly are as a person, ultimately *leading to matches that are based on your true self; Receive a curated selection of potential matches, chosen for you by our Expert Matchmaker.*

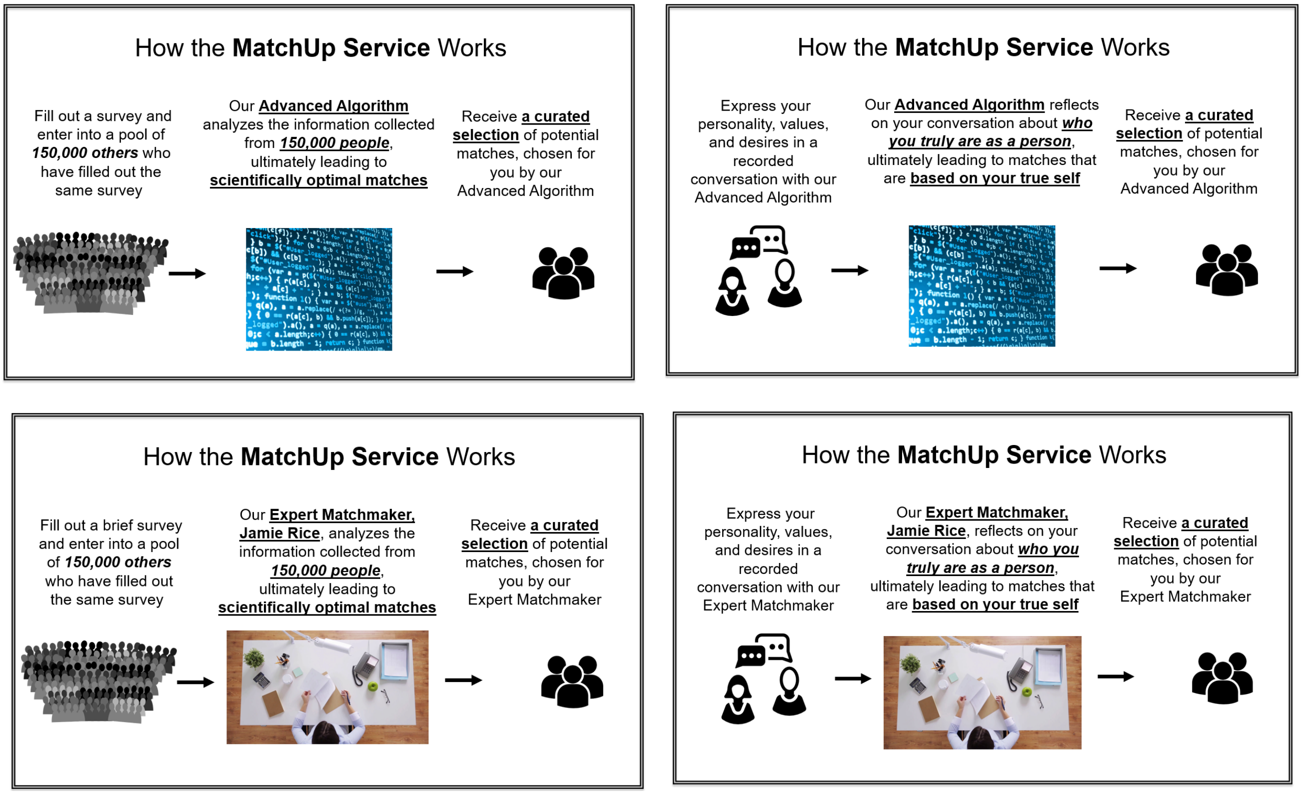

FIGURE 2.8

2 x 2: ALGORITHM VS. HUMAN DECISION MAKER AND QUANTITATIVELY VS. QUALITATIVELY COMPLEX TASK FOR STUDY 4B

We then measured perceptions of the participants' willingness to try the service using the same three-item scale used previously: How likely are you to try out this service? (1 = *Not at all likely*, 7 = *Very likely*); How much would you like to try out the MatchUp service? (1 = *Not at all*, 7 = *Very much*); How likely are you to try MatchUp? (1 = *Not at all likely*, 7 = *Very likely*). Responses to these items were highly correlated (α = .96) and were averaged to create a single composite measure of willingness to try the service.

Results and Discussion

A 2(curator: algorithm vs. human) x 2(type of complexity of decision task: quantitative vs. qualitative)[4] between-subjects ANOVA revealed a significant main effect of decision maker, $F(1, 288) = 7.38$, $p = .007$, but no significant main effect of type of complexity $F(1, 288) = 0.59$, $p = .443$ and no significant effect of the two-way interaction of decision maker and type of complexity, $F(1, 288) = 0.26$, $p = .610$. Simple slopes revealed that, when the decision was qualitatively complex, consumers preferred the algorithm ($M_{\text{algorithm}} = 4.13$, $SD = 1.71$) over the human ($M_{\text{human}} = 3.47$, $SD = 1.80$; $t(154) = 2.35$, $p = .020$, $d = .38$). Similarly, when the decision was quantitatively complex, there was a marginally significant difference in the preference for the algorithm ($M_{\text{algorithm}} = 4.19$, $SD = 1.74$) over the human ($M_{\text{human}} = 3.73$, $SD = 1.71$; $t(134) = 1.53$, $p = .129$, $d = .27$). So, when presented with either a qualitatively or quantitatively-complex decision, the main effect, a preference for algorithm over human decision maker, holds.

[4] The qualitative and quantitative conditions were pretested and were perceived to be significantly qualitatively (M = 5.31, SD = 1.45; t(99) = 9.05, p < .000) and quantitatively complex (M = 5.07, SD = 1.45; t(100) = 7.41, p < .000), respectively.

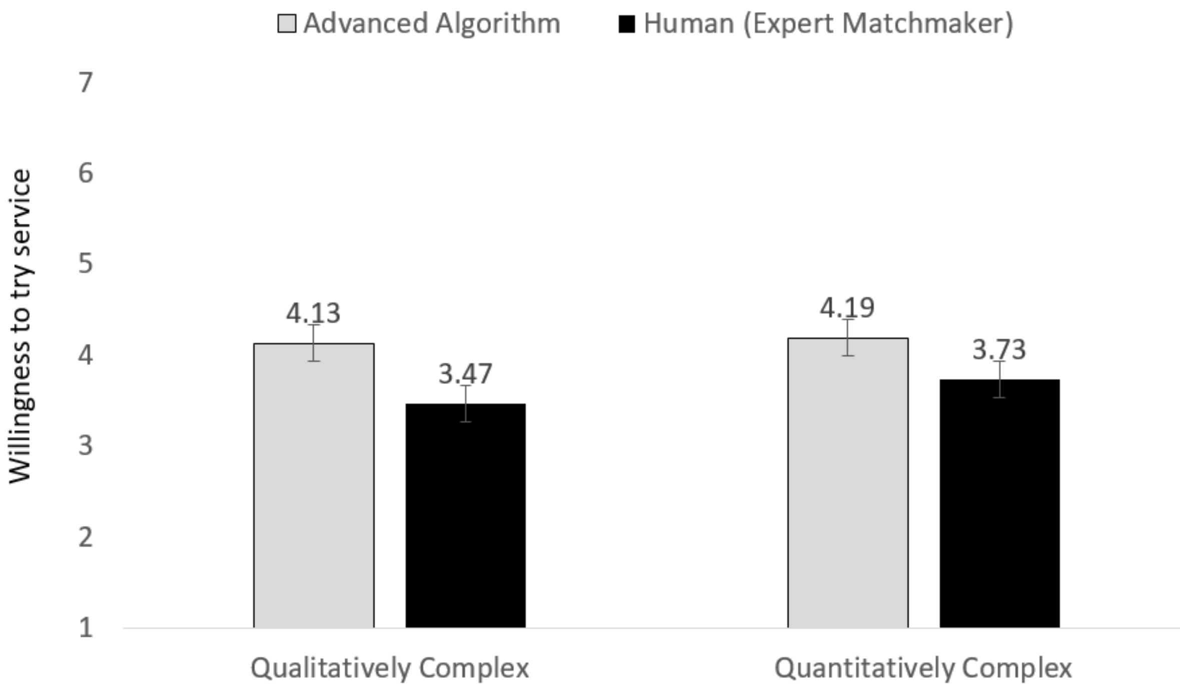

FIGURE 2.9

2 x 2: WILLINGNESS TO TRY SERVICE BY CURATOR (ALGORITHM OR HUMAN) AND TYPE OF COMPLEXITY OF DECISION TASK FOR STUDY 4B

Again, consumers prefer a curated service with items (here, potential dates) chosen by an algorithm rather than a human. This main effect preference holds whether the complexity of the scenario stems from a qualitatively or quantitatively-difficult choice. Though one might expect an algorithm to be preferred to make a "scientifically-optimal choice" from a large assortment size of 150,000, it is perhaps surprising that consumers also prefer the algorithm to make decision that requires understanding "who you truly are as a person." This experiment provides evidence that consumers are comfortable with algorithmic decision-making not only when the decision to be made is quantitatively complex, but also qualitatively complex, even requiring a skill akin to human judgment.

Study 5: Trust as Alternative Explanation

Study 5 addresses the possibility that trust in algorithmic decision-making is an explanation for our previous results. We again look at the preference for algorithmic over human decision-making in the context of a curated service (movie streaming), but also manipulate the participants' trust in the curator (algorithm or expert human) to select good options for them. Thus, this study explores a possible boundary condition of the preference for algorithmic over human decision-making, exploring whether consumers still prefer the algorithm over the human when they have a reason to distrust its/their abilities. Researchers have shown that people become less likely to trust an algorithm after seeing it err, even if the mistake made is equal to one made by a human (Dietvorst, Simmons, and Massey 2014). Thus, consumers lose confidence more quickly in algorithms that make mistakes than with humans who do the same. Our work extends this research to the realm of curation, which is focused on subjective recommendations rather than objective forecasting. Thus consumers may view errors in this context differently than in contexts used in previous research.

Methods

We recruited 397 participants from Amazon's Mechanical Turk and removed 64 participants for failing the attention check[3], leaving a total of 333 participants (M_{age} = 37.1; 58.1% male). In a 2(curator: algorithm vs. human) x 2(low trust condition and control) between-subjects design, participants viewed information about MovieStream, a movie streaming service with films either selected by an Advanced Algorithm or an Expert DJ. We manipulated the

[3] We included attention checks for both the curator of the service and the low trust manipulation. However, participant comments illuminated the fact that the latter attention check could have been misinterpreted, so we only excluded participants based on the former.

participants' trust in the curator; half of participants read a scenario in which the curator had received poor feedback in the past.

First, all participants read the following: *Imagine that you are in the market for a movie streaming application for your phone/computer. You come across MovieStream, an application that provides a curated selection of films for its users.*

Participants in the algorithm x low trust condition then read the following: *Since the service debuted, the film curator, an advanced algorithm, has received some negative feedback about the chosen films. In response, the algorithm's process has been changed to choose films that are better aligned with each customer's precise taste.*

Finally, all participants in the algorithm condition viewed an image of the selection process (see Figure 2.10, image on left) with this description:

> *How the MovieStream Service Works: 1. Watch your favorite movies on your device of choice 2. Your information will be analyzed by our Advanced Algorithm 3. Our Advanced Algorithm considers the creativity, originality and uniqueness of movies in order to choose cinematic gems 4. Receive a curated selection of movies you'll love, chosen for you by our Advanced Algorithm*

Participants randomly selected for the human x low trust condition read the following: *Since the service debuted, the film curator, Jamie Rice, has received some negative feedback about the chosen films. In response, Jamie has changed the process to choose films that are better aligned with each customer's precise taste.*

Finally, all participants in the human condition viewed an image of the selection process (see Figure 2.10, image on right) with this description:

How the MovieStream Service Works: 1. Watch your favorite movies on your device of choice 2. Your information will be analyzed by our Expert Film Critic, Jamie Rice 3. Our Expert Film Critic considers the creativity, originality and uniqueness of movies in order to choose cinematic gems 4. Receive a curated selection of movies you'll love, chosen for you by our Expert Film Critic

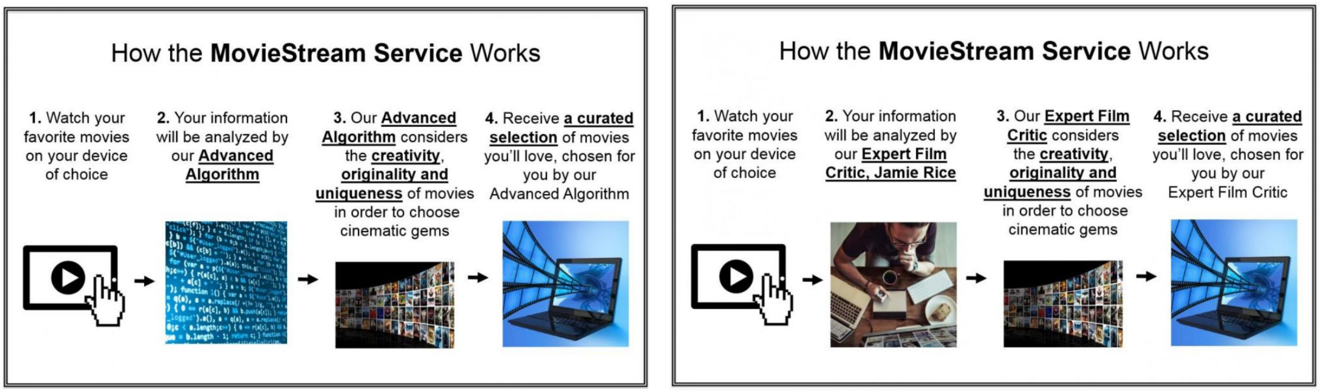

FIGURE 2.10

2 x 2: ALGORITHM VS. HUMAN DECISION MAKER FOR STUDY 5

We then measured perceptions of the participants' willingness to try the service using the same three-item scale used in Study 1. Responses to these items were highly correlated ($\alpha = .97$) and were averaged to create a single composite measure of willingness to try subscription service.

Results and Discussion

A 2(curator: algorithm vs. human) x 2(low trust condition and control) between-subjects ANOVA revealed a significant main effect of curator, $F(1, 332) = 4.56$, $p = .03$, replicating the previously found main effect: a preference for algorithms as curators. Participants in the algorithm condition were more willing to try the service ($M_{\text{algorithm}} = 4.46$, $SD = 1.66$) than those in the human condition ($M_{\text{human}} = 4.11$, $SD = 1.70$; $t(331) = 1.94$, $p = .05$, $d = .21$). Further, a marginally significant main effect of trust $F(1, 332) = 3.49$, $p = .06$ was present. Participants in the control condition were marginally more willing to try the service (M_{control} = 4.45, *SD* = 1.66) than those in the low trust condition ($M_{\text{low\_trust}}$ = 4.14, *SD* = 1.70; $t(331) = 1.65$, $p = .10$, $d = .18$). Importantly, there was a non-significant two-way interaction, $F(1, 332) = .02$, $p = .88$, suggesting that lower trust in the curator does not differentially impact preference for an algorithm vs. a human curated service.

These findings show that when consumers have lowered trust in a decision-maker's ability, stemming from past failures, they are less likely to try a curated service. However, that decreased desire to try a curated service is not different for algorithmic vs. human curators. Thus, in the context of curation, consumers do not lose confidence more quickly in algorithms that err than humans, unlike in objective forecasting contexts where a differential impact on erring algorithms was found (Dietvorst, Simmons, and Massey 2014).

Across six experiments, we have shown that consumers do not demonstrate a preference for human decision-making, but rather prefer algorithmic decision making, especially under complex conditions. Next, we extend our research to the analysis of an archival data set, which provides evidence of the potential backlash that can stem from over-humanization of curated products.

Study 6: Negative Impact of Over-Humanization

It is common practice in the marketplace to "humanize" a product or brand. In Study 4, we examined the impact of a firm's choice to humanize the decision maker behind a curation service. The context of this study focuses on subscription boxes, a type of firm curation in which companies select products for consumers and mail them out at regular intervals. Examples include Birchbox (beauty samples), StitchFix (clothing), BarkBox (pets), and Blue Apron (meal kits). Subscription boxes are a popular business model; an estimated 5.7 million people in the

United States are box subscribers (Steimer 2018). The subscription box market continues to grow; it has increased more than 100% a year over the past five years (Chen at al., 2018).

In describing the curation aspect of product selection, many subscription box firms choose to highlight a particular person (e.g., a celebrity) or a team of people (e.g., "our chefs," "our personal stylists") as having curated the selected products. For example, in the POPSUGAR Must Have subscription box of women's lifestyle products, "every item is hand-picked by POPSUGAR Founder and President Lisa Sugar" (POPSUGAR 2018). Some subscription services are falling in line with the common thinking that consumers prefer "humanized" products/services. However, the results of an archival data study of over 2,000 subscription boxes provided support for the idea that there is a negative impact of humanizing the curator in this way, consistent with our prior theorizing.

Method

Data were collected from the "My Subscription Addiction" website, which catalogs and reviews over 2,000 subscription box services. The site (www.mysubscriptionaddiction.com) receives over a million unique visitors per month (Turner 2017). On the site, subscription boxes are reviewed by site writers. Readers of the site can also log in to give ratings to subscription boxes and to interact with other users of the site. We collected information about all boxes on the website, thus creating a database of 2,000+ subscription box offerings.

The dependent variable is the count of ratings given by site users to the subscription box. The mean number of ratings per subscription box is 9.43 (SD = 29.15). This variable reflects the popularity of the subscription box; those boxes that were rated a greater number of times are more popular than those that were rated fewer times or not at all.

The independent variable of theoretical interest is a dummy variable representing whether the curator of the subscription box is clearly described as a human (e.g., a celebrity, “our chefs,” “personal stylists”) or not described. Other control variables include price, the type of items (full products, samples, full and sample combination, kit), frequency of delivery (less than monthly, monthly, more than monthly), whether the box’s items are standardized for all customers or customized, and whether returning items is allowed.

The dependent variable is a count variable, and the data are over-dispersed (mean = 9.43, variance = 849.72, range: 0 – 479). Therefore, we used a negative binomial regression approach, which accommodates count data with over-dispersion.

Results and Discussion

The results of a negative binomial regression provide evidence that framing the decision maker as a specific person (or team of people), i.e., “humanizing” the curator, has a marginally negative impact on the popularity of the subscription box, relative to boxes curated by the anonymous firm (β= -0.25, SE= 0.13, $p = 0.06$).

Rather than interpreting the beta coefficients, it can be easier to interpret incident rate ratios for negative binomial model results. The estimated rate ratio comparing the anonymous curator to the team/specific person curator while holding the other variables constant in the model is 0.78. Thus, by looking at the incident rate ratios, it can be said that boxes curated by humans are expected to have a popularity rate .22 times lower compared to those curated by the anonymous firm.

TABLE 2.1

NEGATIVE BINOMIAL MODEL RESULTS FROM

DATABASE OF SUBSCRIPTION BOXES (STUDY 6)

	Subscription Box Characteristics Model		
	β	SE	*p*
Price	-0.004	0.00	0.03 *
Type of Items (Full Products)			
Full + Sample	1.08	0.29	<0.001 **
Kit	-0.76	0.21	<0.001 **
Sample	0.48	0.41	0.24
Frequency (less than monthly)			
monthly	-0.69	0.19	<0.001 **
more than monthly	-0.50	0.57	0.38
Standardized			
Customized	0.63	0.14	<0.001 **
Anonymous Firm			
Team/Specific Person	-0.25	0.13	0.06
Returns Allowed (Yes)	1.01	0.24	<0.001 **
Constant	2.67	0.22	<0.001 **
Number of obs		2,069	
Dispersion		mean	
Log-likelihood		-5059.42	
LR $\chi2(9)$		116.64	
Prob> $\chi2$		<0.001	
Pseudo R^2		0.01	

Categorical control variables that had a significant positive impact on the popularity of the box included: a mix of full and sample products (relative to full products only) ($p < 0.001$), customized offerings tailored to the customer (relative to standardized across customers) ($p < 0.001$), and allowing returns of items (relative to not allowing returns) ($p < 0.001$). Two categorical control variables had a significant negative impact on the popularity of the box included: kits (relative to full products only) ($p < 0.001$) and boxes sent monthly (relative to more frequently) ($p < 0.001$). The more expensive the box, the less popular it was as well ($p < 0.05$).

This archival data analysis provides evidence of the potential backlash against the firm's product offering due to over-humanization of the decision maker. Though certainly other aspects of the subscription boxes (e.g., customized rather than standardized, sent monthly, allows returns) are important in predicting their popularity, keeping the "curator" anonymous rather than portraying the curator as a person is an important dimension as well. Importantly, this dimension is easily controlled by the firm in the way that it frames or advertises the selection process behind the curator service. Thus, firms should think twice before choosing to frame the curator as a specific person, which is easily changed in the firm's advertising and promotion.

General Discussion

Across four experiments and one archival study, we found consumer preference for algorithmic over human decision-making in curated services. Study 1 provided a baseline gauge of whether consumers prefer humans or algorithms to make decisions on their behalf in the curation of consumer-packaged goods. In this study, consumers clearly preferred to have an algorithm select products for them. Study 1 provides evidence that consumers are not only willing to accept a curated service (e.g., a subscription box) with algorithmically selected items, but actually prefer it over the same service with items selected by a human.

We test that the preference for algorithms over humans is driven by the belief that algorithms are more competent than humans at managing complex choice sets, including large assortments. Study 2 provides evidence of this process using a mediation approach; when the curator is framed as making a complex decision, an algorithm is the preferred decision maker.

Study 3 then tested the process with a moderation approach by directly manipulating choice set complexity. When faced with making a choice from a very large assortment, consumers preferred to let an algorithm make choices on their behalf rather than a human.

Studies Study 4A and 4B build on this understanding of consumer preference for algorithmic curators in complex choice conditions by exploring two types of complexity:

quantitative and qualitative complexity. Across these two studies, the preference for algorithmic over human curator holds for both qualitatively and quantitatively complex decisions.

Study 5 explores a possible boundary condition for the preference for algorithmic over human curators. Previous research has found that people differentially punish algorithms and humans for making mistakes in objective forecasting, losing trust more quickly in erring algorithms (Dietvorst, Simmons, and Massey 2014). In our research, however, consumers did not punish algorithms more harshly than humans for making mistakes in subjective recommendations (i.e., curating).

Finally, Study 6 provided evidence from an archival study of an online catalog of subscription boxes (N>2,000), that "humanizing" a curated service can have a negative impact on the service. Taken together, these seven studies provide thorough evidence that not only are consumers not adverse to algorithmic curation, but in fact, prefer it over human curation. Our work has implications for both theory and marketing practice, explored in detail below.

Theoretical Implications

The established literature explains that humans have the need to belong to and socially connect with others (Baumeister and Leary 1995, Maslow 1943), which translates to preferring humanized products and brands as well. Indeed, much research in this domain focuses on cases where humanizing products and brands, often through the strategy of anthropomorphism, benefits the firm. Our research builds on the established literature and begins to identify the boundary conditions of pro-humanization. When the task at hand is to sift through many options in order to choose the optimal ones (i.e., a complex decision task), consumers prefer an algorithm, which is more capable at this kind of task, to choose on their behalf.

We show that the preference for algorithms over humans operates through the mechanism of capability. When consumers prefer an algorithm over a human to make choices on their behalf, the underlying operating belief is that algorithms are better than humans at handling complex choice option sets. This is due to the belief than algorithm is better equipped to make a decision amongst a large assortment because it cannot suffer from "choice overload" like a human can. Consumers project their knowledge of "choice overload" onto other humans when considering having another human make a decision from a complex choice option set. In this way, our research contributes to the "choice overload" literature as well.

Our work adds to the literature on anti-algorithm bias, known as "algorithm aversion," with the counterintuitive finding that algorithms may actually be preferred by consumers. Our paper is one of the first to test an algorithm that is tasked with choosing something for the consumer him/herself (see also Yeomans, Shah, Mullainathan, and Kleinberg 2018), rather than forecasting objective outcomes (e.g., Dietvorst, Simmons, and Massey 2014, Logg, Minson, and Moore 2018). Given the increasing prevalence of "recommender algorithms" and curation services in which items are selected for specific consumers, it is important to study algorithms in this context.

Further, our work expands the finding of Dietvorst, Simmons, and Massey (2014) that consumers differentially punish an algorithm more than a human when seeing it/them err when making objective forecasts; in contrast, in the domain of subjective recommender systems (e.g., curation), algorithms and humans are not differentially punished for making errors.

Limitations and Future Directions

Prior work on algorithm aversion has mostly focused on contexts in which a mistake is very costly (e.g., MBA admissions, medical diagnoses). The current research, on the contrary, is focused on domains in which the risk to the consumer is quite low. It is possible that consumer risk may moderate when the consumer is willing to trust decisions made by humans versus machine-based decision makers like algorithms (Dhar 2016). There are real-world examples of when a consumer must choose between algorithm and human advice in contexts with higher risk to the consumer (e.g., algorithmic advice on financial services like selection of a mutual fund). It would be interesting for further research to investigate higher-risk consumer scenarios.

Similarly, the current research focuses on subjective curation contexts, where the consumer is most concerned with receiving curated options (e.g., movies, music) that are most aligned with his/her taste. Curation can also take place in the domain of objective decisions (e.g., financial decisions) where personal taste is not a factor. This may be another interesting context in which to explore algorithmic vs. human curation, and may go hand-in-hand with the idea of more risky decisions, outlined above.

Anecdotally, some consumers have had the opportunity to become comfortable with recommender algorithms in certain domains. For example, on music and entertainments streaming sites like Netflix, consumers are recommended entertainment options they may like; online retailers like Amazon.com provide automated product recommendations. Our research covers the curation-relevant domains of music and movie streaming, online dating, and subscription boxes of consumer goods. These domains were chosen to cover a wide range of areas in which algorithmic curation is often encountered in the marketplace. However, as algorithmic decision-making and advice becomes more commonplace, there may be opportunities to study areas relevant to consumers in which they have not yet been exposed to algorithmic decision-making.

Consumers vary greatly in their access to and comfort level with the internet and technology. Thus, they also vary greatly in their willingness to engage with and trust algorithms to make recommendations or decisions for them. Given the comfort with the internet that is required for participants to engage in mTurk studies, it is possible that our sample is biased towards being more willing to trust algorithms. It will be important for future research to sample from a population that is less savvy in their internet usage, in order to generalize the results more broadly. Education may work as a covariate to capture comfort with technology.

The studies focused on online dating and movie selection operationalized qualitative complexity in the selection of potential matches and “hidden gems” of movies, respectively. Thus our research covered two types of complexity: quantitative and qualitative. However, it is possible that in very qualitative domains in which human judgment is perceived to be irreplaceable by algorithms (e.g., wine, art), a human might be the preferred curator. It would be interesting for further research to delve into such inherently qualitative domains.

Finally, curation is inherently about outsourcing decision-making. We show that in the context of complex decisions, people prefer to have an algorithm make decisions for them, believing the algorithm to be more capable. Thus, capability is an important factor to consider in future research. For example, in domains where people believe themselves to be capable at making good decisions (e.g., actual or imagined wine experts), are they still willing to outsource decision-making to an algorithmic curator when the choice seems very complex? Further research could address the tradeoff between choosing a curator to assist in making a decision versus making one's own choices, and whether a consumer's perceived own capability plays a role.

Managerial Implications

Our research focuses on the domain of curation services, as this is a popular and growing business model and little research has been undertaken to provide direction to such firms. Due to time and energy constraints on consumers' consumption decisions, people are turning to curation services to help them. "Consumers want to author their lives, but they increasingly are looking for ghostwriters to help them out" (Holt 2002, p. 87). Firms have the opportunity to play this role for consumers, adding value to consumers' lives by curating for them. We offer suggestions for firms offering curated products (e.g., subscription boxes) or services (e.g., streaming entertainment) regarding the framing and advertising of "who" is doing the curating.

The question of who to allow to curate for the customer, algorithm versus human, reflects a real tension in the marketplace for consumers. For example, in reviewing two music-streaming applications, Savvides and Orellana write, "Spotify's algorithmic recommendations for new music based on our listening habits is the most on-point. But Apple Music's human-curated radio station often uncovers new or unreleased tracks that also appeal" (2018). Managers may believe that humanizing the curator, especially in cases where algorithmic decision-making is relied upon, is necessary to make consumers more comfortable. However, not only may firms not face a negative reaction to revealing algorithmic decision making, but they may, in fact, suffer a negative impact from over-humanizing the decision maker.

In a music streaming application, for example, curated playlists are drawn from a catalog of 35 million in the case of Spotify, and 45 million for Apple Music (Savvides and Orellana 2018). Thus the use of very large assortments in our studies reflects the "real world" conditions in which curation services offer items selected from giant databases. As shown through our work, when firms are offering curation of very large assortments, it may be especially beneficial for the firm to promote the use of algorithms in their decision-making. This is due to the fact that consumers will believe an algorithm to be more capable than a human at managing such a task.

Managers of all types of firms have based decisions to attempt to humanize their brand or product/service offerings on the assumption that it can only serve as a positive for the company, allowing for better connection with consumers. Examples of this include spokespeople or spokes-animals, as well as anthropomorphizing the brand or the product itself. Technological advances are often humanized, as is the case with the human name and voice of many voice-activated assistants (e.g., Amazon's Alexa, Bank of America's Erica). However, our work provides evidence that, especially in the context of complex decisions, consumers actually prefer to know that an algorithm is handling the decision-making.

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ESSAY 2

INSIGHTS FOR ONLINE PLATFORM FIRMS

FROM SEQUENTIAL CONSUMER SEARCH[1]

[1] A version of this paper is being prepared with coauthors John Hulland, Anindita Chakravarty, and Sara Loughran Dommer for submission to a marketing journal.

Abstract

Though consumer search and choice have been studied for decades, online data allows new insights into consumers' actual search behaviors. The current research examines consumers' sequential search across multiple sessions for a relatively complex and high-involvement product (i.e., an apartment lease). Using a unique firm-supplied consumer search clickstream dataset, the actions of approximately 8,000 consumers are traceable through their entire search process on the website of a platform firm. Platform firms linking buyers and sellers characterize multisided electronic markets (e.g., eBay, Amazon) and are an important and growing part of online commerce. The main research question investigates whether actions taken by searching consumers can be used to identify an increasing likelihood of purchase by search (web browser) session. Results from multi-level logistic regressions with Bayesian estimation provide evidence that consumer actions in sequential search sessions are differentially important in predicting likelihood over time. This research contributes to an understanding of consumer online search behavior for complex and high-involvement products, as well as providing managerial insights for platform firms.

One important way in which consumers' purchase journeys have changed with the proliferation of the Internet is the ability of buyers and sellers to be linked through Internet-based marketplaces. Multisided electronic markets are characterized by an intermediate platform firm that connects buyers and sellers and have been studied for many years (e.g., Bakos 1997).

Though they have existed for decades, online platforms are getting increased attention in both the business press and academic literature. Types of popular digital platforms today include those that mediate work (e.g., Amazon's Mechanical Turk), serve as retail marketplaces (e.g., Amazon, Etsy, eBay), and provide services (e.g., Airbnb, Lyft, Kickstarter, Seamless) (Kenney and Zysman 2016). Herrmann (2017) describes platforms as "the underlying trend that ties together popular narratives about technology and the economy in general. Platforms provide the substructure for the 'gig economy' and the 'sharing economy'; they're the economic engine of social media; they're the architecture of the 'attention economy' and the inspiration for claims about the 'end of ownership'" (Herrmann 2017).

As consumers search for products and services online, their search process creates clickstream data, which is the record of consumers' "clicks" on the Internet (Bucklin and Sismeiro 2009). Given the vast amount of consumer data available for collection today, including this clickstream data, firms have the opportunity to use this data in order to make smarter decisions, construct superior strategies, and bring more value to their customers. Insights about consumers can be garnered from their data and used to make better firm-level decisions.

When firms are able to use consumer data in order to make smart business decisions, it can bring more value to both the firm and its customers. In the case of platform firms, which serve to link buyers and sellers, this increased efficiency can be useful to all parties involved (i.e., buyers, sellers, and the platform itself). In an example of using real estate consumer search data, “Zillow Group has announced the launch of Rental Inform, a data dashboard comprised of exclusive, real-time rental market and *aggregated consumer insight data* aimed to help property management companies make decisions about operations, marketing and investments” (McPherson 2018, emphasis added). Zillow is a real estate platform firm that links buyers with property sellers. So the aggregated consumer data provides information about consumer trends and intelligence, useful to sellers on the platform site.

The focus of the current research to generate consumer insights, based on data representing aggregated consumer search. Importantly, the current research tracks consumers throughout their entire search process, including over multiple browser search sessions. The goal is to uncover the customer search behaviors within sequential search sessions (web browser sessions) that identify likelihood of purchase after that session. A unique dataset has been provided by an apartment brokerage firm (i.e., a platform firm) that traces website actions over a 15-month timeframe by 7,961 customers who were successfully placed in an apartment. This rich data allows a better understanding of what specific consumer behaviors communicate to the platform firm about their likelihood of purchase. We seek to provide insight to platform firms that comes from aggregated consumer search behaviors.

Conceptual Background

Platform Firms

Since the beginning of online commerce, researchers have been interested in the ways that technology can lead to efficiencies for both buyers and sellers. Electronic marketplaces that link multiple sellers with buyers are an example of this; they can reduce buyer search costs by providing many options, resulting in more efficient search (Bakos 1997). The platform can also benefit the sellers by reducing transaction costs for sellers that operate on the site, allowing them to access many potential customers (Hagiu 2014).

As platforms are independent third-party entities that connect buyers and sellers (Kannan and Li 2017), their unique structure and inherent need to balance two sets of customers (buyers and sellers) makes them an interesting context to study. To survive, these platform companies must successfully serve two constituencies to earn revenue (Zhang et al. 2012; Chakravarty, Kumar, and Grewal 2014). Though platforms that link buyers and sellers (e.g., auction houses) have existed for a long time, with the proliferation of this business model on the Internet, much remains to be learned.

Research on platform firms thus far includes work on ways to increase revenue, which is typically collected from sellers on the site through different modes of advertising fees or membership fees, while services are often offered to consumers for free (Lee et al., 2018). Revenue-generation for platform firms that also operate as retailers has been addressed (e.g., Amazon, which sells directly to consumers in addition to operating as a platform, linking buyers and third-party sellers). Researchers have determined which products such platforms should sell directly to consumers and which should be offered through third-party sellers (Jiang, Jerath, and Srinivasan 2011). Further, researchers have studied how platform firms should make marketing resource allocation decisions in the face of cross-market effects (Sridhar, Mantrala, Naik, and Thorson 2011). In a similar vein, the population of sellers can affect the ability of the platform to attract buyers, and vice versa. Disclosing the number of sellers on a platform has been found to help attract additional sellers; sellers prefer markets well populated with sellers, as it attracts greater numbers of consumers (Tucker and Zhang 2010).

Because platform firms operate in multisided marketplaces that present different opportunities and challenges from thoroughly studied dyadic transactions, there is need for further research on marketing variables in platform contexts (Chakravarty, Kumar, and Grewal 2014). "There is still a significant gap in our understanding of the processes within the platforms that can lead to more efficient and effective interactions and outcomes (for both firms and customers/crowd)" (Kannan and Li 2017, p.29). The current research addresses this gap: we seek to use aggregate consumer search data in order to provide insights to platform firms about what those actions signal regarding continued search or imminent purchase. In this way, we treat searching customers as heterogeneous; their unique actions may require different actions from the platform firm.

Clickstream Data

There is a long tradition of studying consumer search and learning but online data allow new insights into consumers' actual search behaviors and journeys to purchase. Clickstream data, "the electronic record of a user's activity on the Internet" (Bucklin and Sismeiro 2009, p. 36), is data that reflects consumers' movement through online space. This type of data has been used by researchers for many years, as it allows rich analysis of online consumer behavior. Clickstream data can be collected across websites (e.g., Bronnenberg, Kim, and Mela 2016) or from one website (i.e., "site-centric"). In the current research, our data are site-centric, containing the actions of consumers on one platform firm.

Relevant research using clickstream data to address questions about platform firms has summarized in Table 3.1, though work in this area has been somewhat limited. Tucker and Zhang (2010) explore how disclosure of seller counts and buyer counts affect seller behavior on platform firms in the face of cross-market effects. Clickstream data are employed to see how potential sellers respond to numerical information about current buyers and sellers on the platform, presented randomly as a field experiment. They find that sellers are more likely to list more when they know that many other sellers also use the platform site, because it is assumed that this will attract more buyers.

Bronnenberg, Kim, and Mela (2016) address consumer online search for a differentiated good (i.e., a good that can be evaluated on many different dimensions, here, a digital camera). This research context differs from most of the prior work with clickstream data, which mostly focused on homogenous and simple products (e.g., books, CDs). Similarly, Kim, Albuquerque, and Bronnenberg (2010) use consumer search data for a similar product (camcorder) on Amazon in order to validate the researchers' model. Bronnenberg, Kim, and Mela (2016) find that when searching for a complex product, consumers were found to search quite extensively, engaging in 14 searches before purchase on average as they search amongst the many dimensions of the product. This differs from previous research on online search behavior which found that consumers engaged in somewhat limited search for products/services including books and air travel (Johnson et al. 2004).

Fang, Li, Huang, and Palmatier (2015) look at the effects of both buyers and sellers on search advertising revenue (sold to sellers and appears in search results for buyers) for the platform. Their research context is a B2B platform across launch and mature stages of operation. Chen and Yao (2017) examine consumers' use of search refinement tools on an online platform firm (travel bookings). They find that refinement tools allow consumers to get more utility from their purchase, and encourage them to search more.

Bronnenberg, Kim, and Mela (2016) and Chen and Yao (2017) incorporate cumulative search into their models, capturing the effect of sequential search over time. Though the current research does not take into account the consumer's cumulative search activity on his/her actions in the focal search session, we do split the data into search sessions to see how activities within sessions change sequentially over time. Therefore, our research takes into account sequential search, but not the effects of cumulative search.

Our research contributes to the work in this area in several ways. First, we model multiple browser sessions per customer. Sectioning the data into browser search sessions is a technique that has been employed by other researchers in this area (e.g., Bronnenberg, Kim, and Mela 2016). Because the number of browser sessions is a variable that is easy for the platform firm to identify (per customer), it is useful to structure studies this way. Though other studies have incorporated cumulative search data into their models, our work is focused on sequential consumer search, in which the count of browser search sessions that have been undertaken, per consumer, is of critical importance.

Our work examines the most differentiated and complex product thus far among the platform search literature using clickstream data. Some work has examined durable goods (e.g., Bronnenberg, Kim, and Mela 2016 look at digital cameras; Kim, Albuquerque, and Bronnenberg 2010 look at camcorders), which is different from the original work using clickstream data, which mostly examined homogenous and simple products (e.g., books, CDs). The focus of the current work (i.e., apartment lease market) is very complex, multi-faceted, and by far the most expensive product examined by researchers in this area.

Finally, we are interested in using aggregate customer data in order to provide insight for the platform firm on how to actively accelerate customer purchase. Tucker and Zhang's (2010) work offers some insight on how much the platform may choose to disclose about its count of buyers and sellers; Fang et al. (2015) mention ways that the platform can best manage its user base, on both the seller and buyer side. Our work differs from theirs in the focus on insights pulled from aggregate consumer data.

Our research explores one main question: Can consumer online sequential search behavior identify likelihood of purchase within a search session? We model consumers search processes until they purchase. Overall, we model 20+ browser search sessions as consumers actively search on the online platform firm for a complex product. Specifically, we examine six relevant dimensions of online sequential consumer search: search breadth and depth, interactions with search and experience attributes, and building and winnowing a consideration set, explained in more detail below.

Dimensions of Online Search

Search and experience attributes. The current research uses the “search/experience paradigm” to understand how consumers might view and interact with the many dimensions of a complex product purchase. When consumers can evaluate an attribute of a product prior to purchase, it is known as a “search” attribute; when an attribute of a product cannot be evaluated prior to purchase because it requires the consumer’s personal experience with the product, it is an “experience” attribute (Nelson 1970, 1974). For example, when purchasing a car, search attributes include average miles per gallon and number of seats, while experience attributes include comfort of the car on a long trip. Products can be classified as either a search or experience good due to the classification of the dominant attributes of that product (Klein 1998), though the current research examines both search and experience attributes of one complex product.

Researchers have been interested in how this classic consumer search paradigm extends into the online environment. Though Klein (1998) argues that the great amount of information available online, including feedback from other consumers' personal experiences, turns many experience attributes into search attributes, others have found the paradigm useful in understanding online consumer behavior. For example, it has been found that consumers have different online search behavior for search versus experience goods, including depth of search, breadth of search, free riding behavior, and interaction with product reviews (Huang, Lurie, and Mitra 2009). Further, Weathers, Sharma, and Wood (2007) suggest that online retailers' communication strategies should vary based on whether the product is a search or experience good: experience qualities can be communicated to online shoppers through visual images, while search qualities should be promoted with much detailed information.

Search attributes (e.g., price) are objective and easily compared across products, while experience attributes are subjective and more difficult to compare across products (Huang, Lurie, and Mitra 2009). So, search attributes are more easily accessed by searching consumers, whereas experience attributes would require more effort from the consumer. Thus, we propose that, in a single search session, interacting with search attributes would signify that a consumer may still be gathering information and relatively early in his/her search process. In order to conserve resources, people often simplify the early search process by focusing on a few key search attributes, rather than immediately sifting through all available information. This makes the process more efficient and less cognitively costly. Conversely, engaging with experience attributes in a search session would signify that a consumer is willing to spend the effort required to absorb this information and is likely to purchase soon. We expect the following:

H_1: The more a consumer interacts with search attributes within a focal search session, the more likely he/she is to continue search in a subsequent session.

H_2: The more a consumer interacts with experience attributes within a focal search session, the less likely he/she is to continue search in a subsequent session.

Search breadth and depth. Search breadth and depth are dimensions commonly used to measure a consumer's search activity. These measures are higher-order measures of consumer search and are not concerned with the actual activities (i.e., "clicks") undertaken during the search session (e.g., search and experience attributes). Breadth of search reflects how widely a consumer is searching; breadth of search can be operationalized by the number of web pages viewed (e.g., Huang, Lurie, and Mitra 2009), the number or type of sources used, or the number of alternatives evaluated (Klein and Ford 2003). As the current research is focused on clickstream data from one platform firm, we use the number of alternatives evaluated to reflect the consumer's breadth of search. Search depth is reflected by the amount of time a consumer spends searching (Huang, Lurie, and Mitra 2009).

Given that a consumer must gather information about many available options before he/she can make a final decision, we propose that a wide breadth of search will signify that a consumer is still actively searching and not yet ready to purchase. As the consumer narrows in on a final choice, it seems likely that he/she would be then be willing to spend more time (in one browser session). Thus, we expect the following:

H_3: The wider the consumer's breadth of search within a search session, the more likely he/she is to continue search in a subsequent session.

H_4: The greater the consumer's depth of search within a search session, the less likely he/she is to continue search in a subsequent session.

Consideration set. Researchers have long accepted the framework of a consideration set (also known as a "choice set") to understand how consumers make a final purchase choice from among many options (Howard and Sheth 1969). Consideration sets are a group of considered product options (a subset of all available options) from which a consumer will make his/her final purchase choice (Mehta, Rajiv, and Srinivasan 2003).

Though consideration sets have been, in the past, not directly observable to researchers (Shocker, Ben-Akiva, Boccara, and Nedungadi 1991), online clickstream data makes it more possible to observe the consumer's decision-making process as he/she builds and edits a list of "favorite" options.

From all of the available options, a consumer chooses the subset of items that he/she will consider more seriously to purchase and will gather more information about (Kardes, Kalyanaram, Chandrashekaran, and Dornoff 1993). When the consumer is in the stage of adding options to the list that he/she would like to research further or know more about, it is likely that he/she still has work to do before making a final decision.

On the other hand, when a consumer is closer to making a final decision, he/she may edit the consideration set, winnowing down the list of options. Removing a previously considered option from the consideration set, like unmarking a product option as a "favorite," is akin to physical acts of closure studied by Gu, Botti, and Faro (2013) that can help a consumer feel more satisfied with his/her final choice. Given this, we propose that adding "favorited" options will signify an ongoing search process, while winnowing down a consideration set (by removing "favorited" options) will signify imminent purchase. We expect the following:

H_5: The more product options a consumer adds to his/her consideration set within a search session, the more likely he/she is to continue search in a subsequent session.

H_6: The more product options a consumer removes from his/her consideration set within a search session, the less likely he/she is to continue search in a subsequent session.

Methods

Data Context

The empirical context of the current research is the apartment lease market in a major metropolitan area in the United States. According to the Joint Center for Housing Studies of Harvard University (2015), the homeownership rate in the United States has continued to fall since its peak in 2004, meaning that more people are turning to apartment rentals for their housing needs. Additionally, the percentage of renters paying more than 30% of their income on housing hit a new record high in 2014 (Joint Center for Housing Studies of Harvard University 2015). Thus, an expensive rental option is an increasingly common housing choice for Americans, and therefore a consequential area for research.

An apartment brokerage firm represents a platform firm that links apartment companies (sellers) and potential renters (buyers) through its website. Platform firms can earn revenue by either taking commissions or generating advertising revenue (Fang et al. 2015). In this case, as is the case with many platform firms, the service is offered for free to consumers and the platform firm collects profits from the sellers, offering their services for free to customers (Lee et al., 2018). In this context, apartment complexes provide a commission to the platform for their referrals. Thus, the platform is incentivized to serve two constituents: potential renters and apartment firms. The platform firm will be most successful when matches between buyers and sellers can be made efficiently, as revenues from commissions are realized sooner.

Data and Measures

Our clickstream data, provided by an apartment brokerage firm, includes all of the actions of customers, who are traceable by a unique identification variable, on the apartment broker's website over a 15-month timeframe (April 2015 - June 2016). During this time, 7,961 consumers were placed in over 900 different apartment complexes.

All customers who signed a lease with an apartment ("purchased") during this timeframe are included in the model. As our work is interested in how search activities are related to choice/purchase, we follow the example of other researchers in this area (e.g., Chen and Yao 2017; Bronnenberg, Kim, and Mela 2016) and include only those consumers who purchased during the timeframe of the clickstream data in the final dataset.

In this firm-provided, clickstream dataset, we have the ability to analyze consumers' sequential and discrete search sessions (web browser sessions). Consumers are provided an intial personalized list ("portfolio") of apartments by a salesperson, among which they can search for an apartment ($\bar{x}$ = 57 properties, range = 1 – 812). On average, customers interacted in detail with 31 of these properties (e.g., looking at floorplans, reviewing prices). Consumers search among these properties until they sign a lease with an apartment ("purchase").

Dependent variable. The dependent variable of interest is whether the customer purchased after the focal browser search session (1: purchased, 0: continued searching). Customers' count of browser search sessions on average is 9.9 (s^2 = 283.6, range = 1 – 584) before purchase. The distribution of how many customers are actively searching in each browser session is shown in Figure 3.1; for example, if a customer completed four browser search sessions before purchasing, he/she would be active in the data through "Session 4."

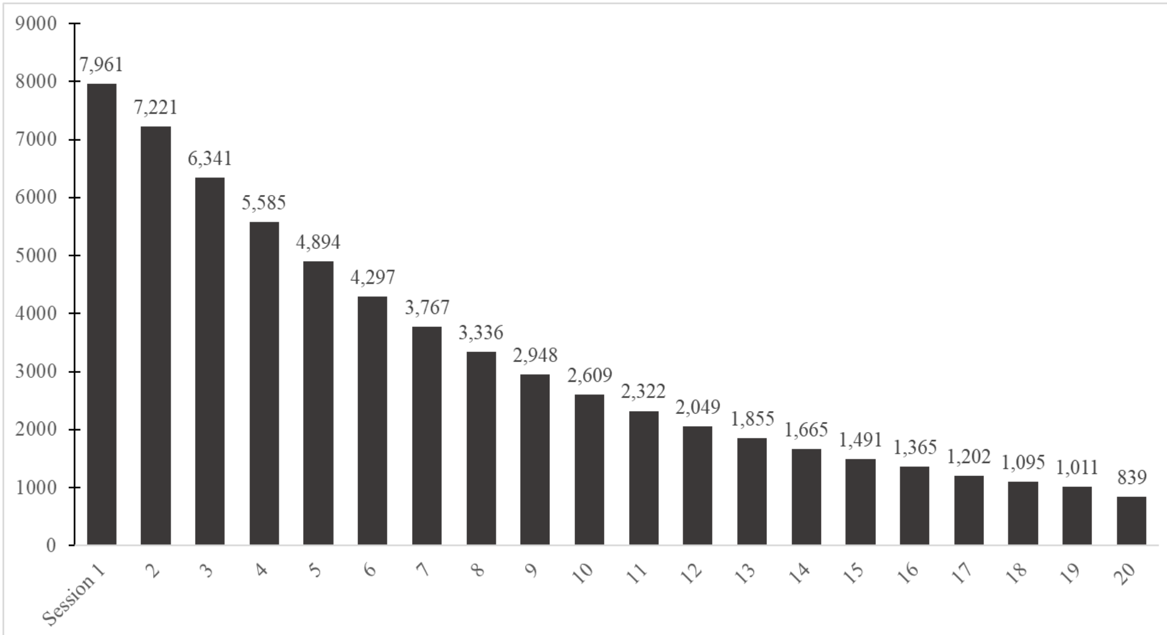

FIGURE 3.1

COUNT OF ACTIVE SEARCHING CONSUMERS PER BROWSER SESSION

Graph 1 shows a relatively steady decay over time, representing a steady proportion of people are purchasing (i.e., terminating the search process) after each subsequent browser search session. After their first search session, 9% of customers (among those who will eventually purchase) make their selection. Among those who did not purchase after their first search session, 12% of consumers purchase after their second search session. Proportions of purchasers after each search session, through 12 sessions, is shown in Table 3.2. Thus, without any additional information, the platform firm would expect about 11-12% of the searching consumers to purchase at the end of each browser session.

TABLE 3.2

COUNT OF SEARCHING CONSUMERS AND PROPORTION

OF PURCHASERS PER BROWSER SEARCH SESSION

	N=	Proportion who sign a lease
Session 1	7,961	0.09
Session 2	7,221	0.12
Session 3	6,341	0.12
Session 4	5,585	0.12
Session 5	4,894	0.12
Session 6	4,297	0.12
Session 7	3,767	0.12
Session 8	3,336	0.11
Session 9	2,948	0.12
Session 10	2,609	0.11
Session 11	2,322	0.11
Session 12	2,049	0.12

Independent variables. As we model the data by browser search session, the independent variables are all consumer actions that take place during an individual browser session.

Consumers are able to perform several actions in order to gather information about apartments. These attributes were categorized into search and experience attributes by five marketing expert coders (77% agreement across all measures); actions classified by a majority as search or experience attributes were labeled as such. Search attributes are those that provide straightforward information that can be fully grasped before purchase: the location of the apartment (viewing maps), the monthly price (viewing pricing details), and the number of bedrooms, bathrooms, and the general layout of the apartment (viewing floorplans). Experience attributes, on the other hand, provide richer information that is harder to grasp before purchase: detailed photos of the apartment that show the style of it (viewing photos), the feel of the neighborhood (looking at the street view), and subjective information about others' experiences there (reading reviews). Details of the actions categorized as search or experience are listed in Table 3.3.

TABLE 3.3

CATEGORIZATION OF SEARCH ACTIONS

Action	Attribute
Viewing floorplans	Search
Viewing pricing details	Search
Viewing maps	Search
Viewing photos	Experience
Looking at the street view	Experience
Reading reviews	Experience

Search breadth, how widely a consumer is searching, is operationalized by the count of properties interacted with within a session. Search depth is reflected by the time spent searching (in minutes) within a single search session.

Consumers are able to mark properties in their portfolio as "favorites," reflecting their consideration set. Marking a property as a "favorite" adds to the consideration set and removing a property as a "favorite" winnows down the consideration set. Details of the distribution of each of these measures across search sessions can be found in Appendix A.

TABLE 3.4

DESCRIPTIVE STATISTICS OF INDEPENDENT VARIABLES

	$\overline{x}$	s
Search attributes (count of actions)	3.6	6.7
Experience attributes (count of actions)	5.9	13.9
Search breadth (properties interacted with)	6.7	12.4
Search depth (minutes)	14.5	3.3
Adding property to consideration set	0.7	2.4
Removing property from consideration set	0.2	1.0

Models and estimation. Parameters were estimated for each sequential browser search session. For example, all consumers have a first search session (N=7,961). For those who did not purchase after their first search session, they undertake a second search session and are thus included in the next model (N=7,221). We continued this modeling procedure for 20 search sessions (N=839), which covers about 90% of the data.

Multilevel logistic regression was employed to model the data, as it allows for a binary dependent variable (i.e., 1 for purchase after that browser session or 0 for continued search) and for random intercepts at consumer level, reflecting the multilevel structure of the data (i.e., browser sessions are nested in consumers).

We use Bayesian estimation of the model using “bayes: melogit” command in Stata 15. This Bayesian approach allows the means and variances (per independent variable) uncovered from one browser session serve as the informative priors for the next browser session. Because we are modeling sequential search sessions, this allows the information gained in one session model to be used in the next. (In the first browser search session model, we use priors ~ normal (0,1) for the independent variables and ~ normal (0,100) for the constant.) MCMC burn-in is 2,500 and MCMC sample is 10,000 for all models.

Results

Results from the first seven browser search sessions are presented as odds ratios in Table 3.5 and Figure 3.2. Starting in Session 4 and going through Session 20, results are very steady and remain consistent over time, so this information is not reported. Thus, the impact of the different dimensions of search behavior are steady over time if consumers continue to search four sessions or beyond.

Odds ratios can be interpreted as follows: Holding the other values constant, we will see an increase in the odds of purchasing after the first session of 15% for each property removed from the consideration set (removed as a “favorite”) and of 3% for each experience attribute. Further, we will see a decrease in the odds of purchasing after the first session of 3% for each additional property viewed (session breadth) and of 5% each for each property added to the consideration set (added as a “favorite”) and for each search attribute, holding the other values constant. Session depth (measured in minutes) was not significant in the first search session. Random intercepts were included at the customer level in order to capture variance per customer.

TABLE 3.5

ODDS RATIO RESULTS FOR SEARCH SESSIONS 1 - 7

	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Session 7
	N = 7,961	N = 7,221	N = 6,341	N = 5,585	N = 4,894	N = 4,297	N = 3,767
Session depth	1.00	1.01	1.02*	1.02*	1.02*	1.02*	1.02*
(standard deviation)	(0.01)	(0.01)	(0.007)	(0.01)	(0.01)	(0.01)	(0.01)
Session breadth	0.97*	0.97*	0.97*	0.98*	0.98*	0.98*	0.98*
	(0.01)	(0.01)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Increase cons. set	0.95*	0.95*	0.94*	0.94*	0.94*	0.94*	0.94*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Reduce cons. set	1.15*	1.10*	1.07*	1.06*	1.05*	1.06*	1.05*
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Search attributes	0.95*	0.95*	0.95*	0.95*	0.95*	0.94*	0.95*
	(0.01)	(0.01)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Experience attributes	1.03*	1.02*	1.02*	1.02*	1.02*	1.02*	1.02*
	(0.01)	(0.01)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
constant	0.18*	0.16*	0.17*	0.17*	0.17*	0.17*	0.16*
	(0.01)	(0.01)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Random intercepts	0.03*	0.16*	0.01*	0.04*	0.07*	0.10*	0.08*
	(0.07)	(0.05)	(0.004)	(0.02)	(0.03)	(0.03)	(0.03)

*significant (i.e., 95% CI does not cross 0)

Figure 3.2 shows the odds ratio results for the six independent variables across the first seven browser search sessions. Three of the independent variables were consistent positive signifiers of purchase: removing a property as a “favorite,” search depth (minutes spent searching), and experience attributes. Removing a property as a “favorite” is the strongest signifier of purchase, but has a decreasingly positive impact on imminent purchase in the first three sessions. Thus, the impact of this variable is greater earlier in the consumer’s search. Depth of the search (reflected in the minutes spent searching) becomes significant in the third search session. Experience attributes has an impact similar to depth of search, and is significant in all seven sessions.

The impacts of three of the independent variables were negative (i.e., signifying continued search): search breadth, search attributes, and adding a property as a "favorite." All three of these negative signifiers of purchase had steady impacts across the seven search sessions and were significant in each.

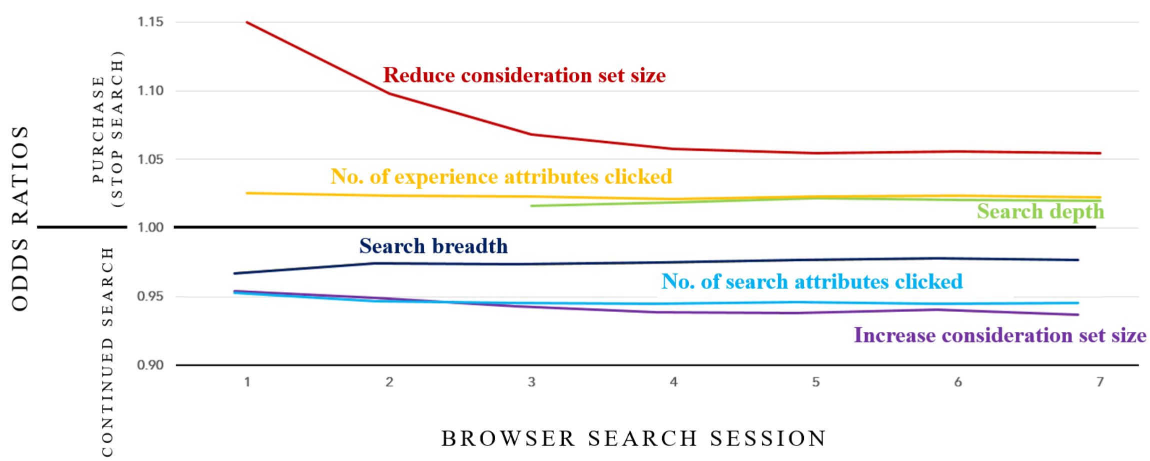

FIGURE 3.2

ODDS RATIO RESULTS FOR SEARCH SESSIONS 1 - 7

Search and experience attributes

Because information about search attributes is more easily acquired by searching consumers, we hypothesized that interacting with search attributes would signify that a consumer may still be gathering information and relatively early in his/her search process. Support was found for this hypothesis consistently across the search sessions.

Because gathering information about experience attributes requires more effort from the consumer, we hypothesized that engaging with experience attributes would signify that a consumer is willing to spend the effort required to absorb this information and is likely to purchase soon. Support was also found for this hypothesis consistently across search sessions.

Search breadth and depth

We hypothesized that search breadth, which represents how widely a consumer is searching (operationalized by number of properties interacted with), would be wider as the consumer is still gathering information about many available options. Support was found for the notion that consumers would have wider search breadth before they are ready to purchase.

We hypothesized that as the consumer narrows in on a final choice, he/she would be willing to spend more time (in one browser session), so a greater search depth (operationalized by time spent in one browser session) will signify imminent purchase. Support was found for this hypothesis across browser sessions.

Consideration set

We hypothesized that adding to the consideration set would signify that the consumer is still consideration many options and has work to do before making a final decision. Support was found for this hypothesis throughout the search sessions.

On the other hand, when a consumer is closer to making a final decision, he/she may reduce the consideration set so we hypothesized that this action may signify imminent purchase. Support was found for this hypothesis as well. In fact, in the first three search sessions, reducing the consideration set was the strongest signifier of imminent purchase, though its influence decreased over the first three sessions and then remained steady. So, if the platform firm sees a consumer willing to narrow the consideration set early in his/her search sessions (here, by removing a property that was previously marked as a favorite), that would be a very strong signal that a purchase will be made soon.

Implications

From these results, we advise that the platform firm has the opportunity to intervene with the searching consumer in a way that will make purchase more efficient. When the consumer is engaging in the three actions (independent variables) that are consistent positive signifiers of purchase – removing a property as a “favorite,” search depth (minutes spent searching), and experience attributes – it is likely that he/she is likely to make a purchase soon. Thus, it would be an appropriate time for the salesperson to step in and help finalize the purchase. In the case of this particular platform firm, it receives a commission as long as the consumer remembers to mention the service when signing a lease. Therefore, the salesperson would be well-advised to take that opportunity to remind the customer to mention the platform service when they are close to purchase.

When the consumer is engaging in the three actions (independent variables) that are consistent negative signifiers of purchase – search breadth, search attributes, and adding a property as a “favorite” – the platform salesperson might take the opportunity to offer assistance. As these types of actions signal that the customer is still actively searching and not likely to purchase soon, it is possible that assistance from the salesperson would help speed up the search process. These types of nudges from the salesperson, based on the consumer’s active search behavior, could help bring efficiency to the search and purchase process.

Discussion

Using site-centric clickstream data produced as consumers search on a platform firm’s site for a complex product, we uncover several consumer search measures that predict continued search (or imminent purchase) in a consumer’s browser search session. The current research is a first step in understanding which customer actions signify imminent purchase, in order for the platform firm to better encourage or facilitate those actions.

Apartment rentals are complex products that can differ greatly among many different dimensions (e.g., price, location, features, and layout). Choosing an apartment rental is a complex and high-involvement decision context, so our results can generalize to similar complex and high-involvement product contexts (e.g., cars, appliances).

Importantly, one focus of the current research is to tie consumer psychology knowledge to online search behaviors and firm-relevant insights. For example, consumers removing options from their consideration sets was a strong signifier of imminent purchase. Prior research has shown that consumers engaging in physical acts of closure, studied in the offline context, in order to minimize regret and increase choice satisfaction (Gu, Botti, and Faro 2013). Our work shows the possibility that consumers also engage in voluntarily "physical" acts of closure online as well, possibly for the same reasons.

Managerial Implications

Very little research has addressed issues relevant to the platform firm itself, so there is the potential for important strategic managerial relevance for platform firms to be gained from the current research. Because platform firms that earn revenue through commissions do so when successful matches are made between buyers and sellers, the platform would wish to make these matches as efficiently as possible. Thus, the current research seeks to provide important insight for platform firms into how to accelerate purchases (i.e., successful matches between buyers and sellers), which adds value for all involved parties. Specifically, we suggest appropriate nudges from the salesperson when they see certain behavior from consumers, which signals either imminent purchase or likely continued search. Further, our work is representative of managerial insights that can be from aggregate consumer data, a relevant way in which firms are operating today.

Limitations and Further Research

Given that our work stems from data provided by one platform firm, it would be useful to compare these results to data from other firms. As with other research that uses site-centric clickstream data, the main drawback from this type of data is the lack of information from consumer's search activity on other websites (and, to a lesser extent, in person) (Bucklin and Sismerio 2009).

The customers of the platform firm are able to search amongst an initial set of options provided by the salesperson at the firm. This set of products (here, apartment properties, called a "portfolio") comprises all the properties that the customer is able to view and interact with. Thus, the customer's consideration set is a subset of this initial, firm-provided set of options. Because the firm's salespeople are tasked with determining this initial set for consumers, it raises the question of what factors influence the size of the set. These factors are explored in Appendix B.

Though consumers are certainly heterogeneous in many ways, it is possible that consumers who purchase after similar counts of browser search sessions may be fundamentally similar to one another or different from other groups of consumers. Appendix C explores several variables segmented by consumer groups.

Our work begins to offer suggestions to the platform firm about possible interventions, signaled by specific consumer actions, that would be beneficial for it to take in order to increase search and purchase efficacy. It would be extremely useful for future research to validate these suggestions through a field experiment. Doing so would also allow for boundary conditions to be found for platform intervention as well: Is there an ideal number of times for the platform firm to intervene? Does intervention actually lead to more efficient search and purchase process? Are consumers more or less satisfied with their final purchase choice when the platform firm has assisted their search process? Much remains to be researched in this interesting research domain of active, rather than passive, platform firms.

Finally, in order to best assist the platform firm in providing value to consumers, it will be necessary to take the results generated here and turn them into a more managerially-helpful tool. In the current research, we use aggregated consumer search data to identify which consumer website actions signify continued search or imminent purchase. However, from a firm point-of-view, consumers are likely to engage in many different types of actions within their search sessions. Thus, the ability to collapse information across types of actions would allow us to "score" individual customers on how close he/she is to purchase per browser session. This would allow the firm to gain a more useful understanding of how each individual customer is progressing on his/her path to purchase and how the salesperson can best intervene.

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Appendix A

The following four graphs (Figures 3.3 – 3.6) show the average number of times searching consumers "clicked" on the following actions: an action categorized as an "experience attribute," an action categorized as an "search attribute," adding a property to the consideration set, and removing a property from the consideration set. Figure 3.7 shows search breadth, operationalized by number of properties interacted with (i.e., how widely the consumer is searching) and Figure 3.8 shows search depth, operationalized by time spent searching (in minutes).

With the exception of reducing the consideration set size, all other measures were highest in the first browser search session, pointing to this highly active search session as an essential one.

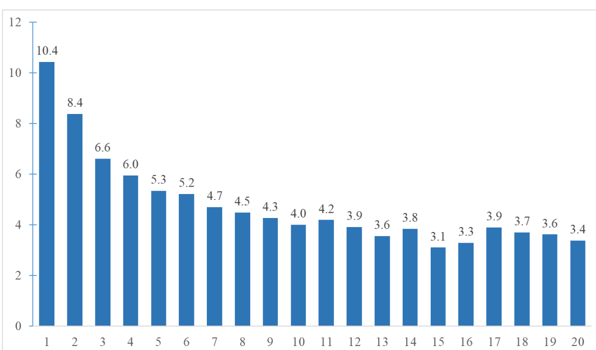

FIGURE 3.3
NO. EXPERIENCE ATTRIBUTES CLICKED

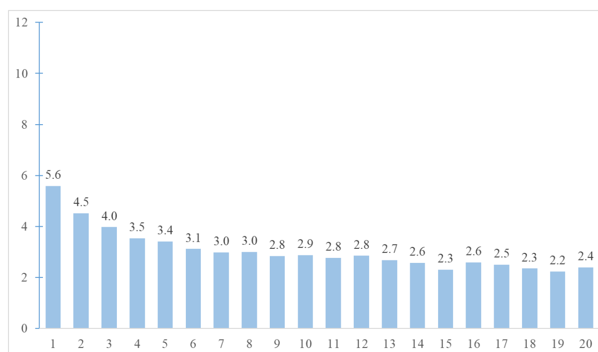

FIGURE 3.4
NO. SEARCH ATTRIBUTES CLICKED

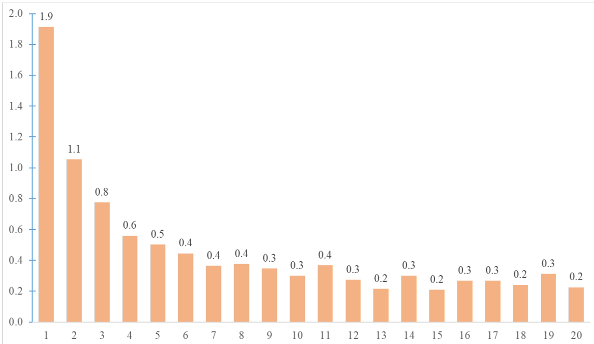

FIGURE 3.5
INCREASE CONSIDERATION SET SIZE

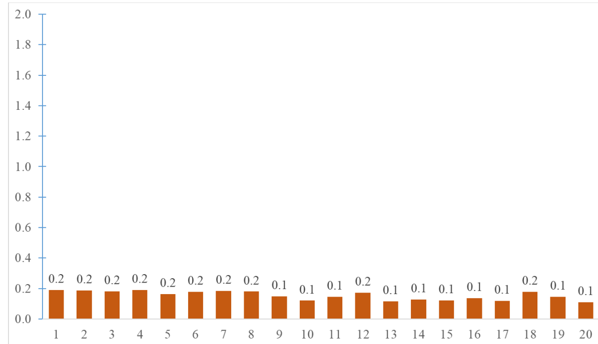

FIGURE 3.6
REDUCE CONSIDERATION SET SIZE

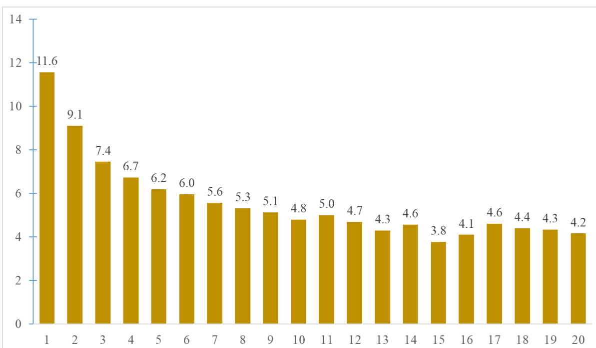

FIGURE 3.7
SEARCH BREADTH (COUNT OF PROPERTIES)

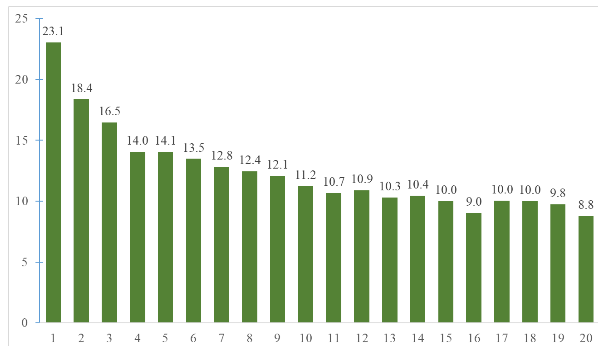

FIGURE 3.8
SEARCH DEPTH (MINUTES)

Appendix B

The customers of the platform firm are able to search amongst an initial set of options provided by the salesperson at the firm. This set of products (here, apartment properties, called a "portfolio") comprises all the properties that the customer is able to view and interact with. Thus, the customer's consideration set is a subset of this initial, firm-provided set of options.

Because the firm's salespeople are tasked with determining this initial set for consumers, it raises the question of what factors influence the size of the set. Consumers provide the salesperson with some information about their specifications (e.g., location preference) before the salesperson supplies them with the initial set of options.

Given that the dependent variable is number of properties in the initial set (a count variable) and that the variance of the dependent variable is much greater than the mean, we turn to a negative binomial model to model the data. The initial set ranges from 1-812 properties, with an average of 56.8 properties (variance of 2,027.2). Figure 3.9 shows the distribution of the initial set size.

All 14,408 customers were included in the model (some customers were missing maximum budget or search timeline information). Independent variables included the following: the source of the lead (client contacted directly, internet listing service, search engine paid ads, or visited a store location in person), the client's maximum monthly budget, the client's search timeline (the weeks from the customer's first contact to their desired move-in date). A salesperson variable was included to capture differences unique to each salesperson, as well.

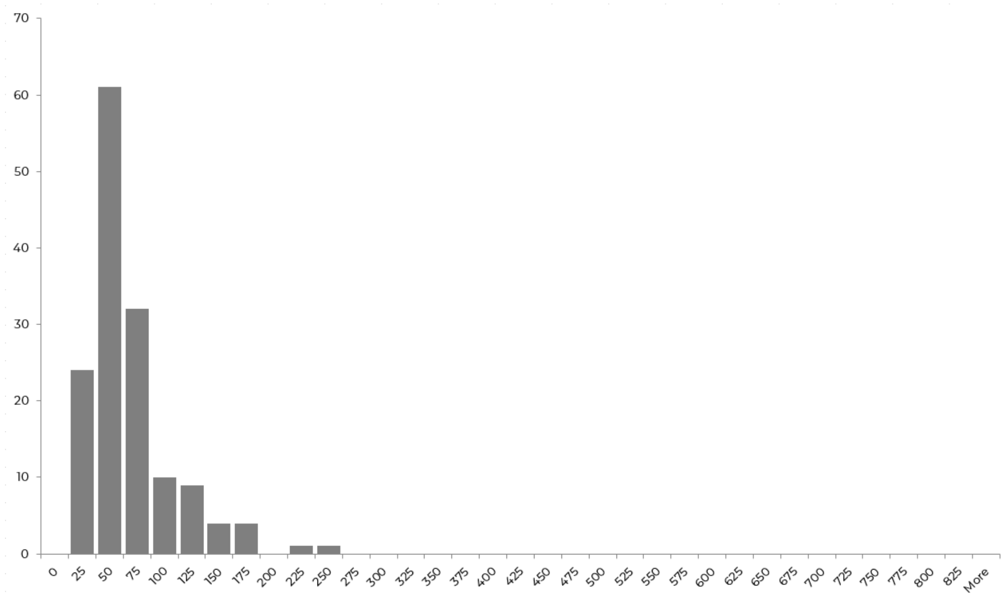

FIGURE 3.9

DISTRIBUTION OF INITIAL SEARCH SET SIZE

We estimated the negative binomial model using Stata v. 14. The results of a likelihood ratio test (that alpha, the overdispersion parameter, equals zero) provides strong evidence that alpha is non-zero and that the negative binomial model is a superior choice to the Poisson model. Coming from an Internet listing service (relative to contacting the firm directly) had a significant, negative impact on the size of the initial set. As the customer's search timeline increased, their initial set increased. Also, as the customer's maximum monthly budget increased, their initial set increased. This information may be useful for the salespeople to know, as it may highlight ways in which they are treating clients differently, depending on how they first come to the company, their budgets, and their search timelines.

TABLE 3.6
NEGATIVE BINOMIAL MODEL RESULTS

N=14,408
DISPERSION: MEAN
LOG LIKELIHOOD: -69,568.6
LR CHI2(190): 2874.8
PROP > CHI2: <0.001
PSEUDO R2: 0.02

	β	Std. Err	p>|z|
Salesperson	various		
Lead Source (Client contacted)			
Internet Listing Service	-0.1	0.02	<0.001 **
SEM (Google, Bing paid ads)	-0.02	0.02	0.25
Visited Store	-0.03	0.02	0.09 *
Maximum Budget (in $100s)	0.01	<0.01	<0.001 **
Search Timeline (in Weeks)	0.02	<0.01	<0.001 **
Constant	3.73	0.64	<0.001 **
α	0.39	<0.01	

Appendix C

Consumers who purchase after similar counts of browser search sessions may be fundamentally similar to one another or different from other groups of consumers. Consumers were grouped via quaternary split into those who purchase after 1-2 browser search sessions (N=1,708), 3-5 sessions (N=2,062), 6-10 sessions (N=1,917), and 11 or more sessions (N=2,274). The consumers were grouped in order to have roughly the same numbers of consumers in each group.

From this consumer segmentation, we find that the four groups of consumers did not seem to differ in their maximum apartment budget. However, differences in search timeline (i.e., the time from signing up with the apartment brokerage firm until their desired move-in date) were found by consumer cohort: the longer the consumer's search timeline, the greater the number of search sessions before close. Additionally, the greater the number of properties in the consumer's portfolio (comprising all of their options on the site), the greater the number of sessions consumers searched before purchase.

TABLE 3.7
MEANS BY CONSUMER SEGMENTS

	1-2 browser sessions	3-5 browser sessions	6-10 browser sessions	11+ browser sessions
	N=1,708	N=2,062	N=1,917	N=2,274
Maximum monthly budget (mean)	$1,110	$1,122	$1,131	$1,132
Search timeline (mean)	27 days	31 days	38 days	44 days
Properties in portfolio (mean)	46	53	59	73

TABLE 3.1
SUMMARY OF RELEVANT PLATFORM AND CLICKSTREAM LITERATURE

Title	Authors	Year	Research Context	Platform	Decision Complexity	# Search Sessions	Method	Key Points	Study size
Sequential Search with Refinement: Model and Application with Click-Stream Data	Chen and Yao	2017	Travel website (hotel bookings)	Yes	Somewhat	Multiple	Structural model	Using search refinement tools on an online platform firm allows consumers to get more utility out of their purchase, and they search more	N = 495 consumers over 2 weeks looking in 4 cities, purchasers only
Zooming In on Choice: How Do Consumers Search for Cameras Online?	Bronnenberg, Kim, and Mela	2016	Online digital camera retailers (Amazon, Walmart, Best Buy)	Yes - Amazon	Somewhat (durable good)	Multiple (14 on average)	Multiple models using panel data	Consumers search extensively; Early search behavior is very predictive of final product choice	N = 967 buyers, purchasers only
Direct and Indirect Effects of Buyers and Sellers on Search Advertising Revenues in Business-to-Business Electronic Platforms	Fang, Li, Huang, and Palmatier	2015	B2B electronic market	Yes	Somewhat (durable goods)	N/A	VAR model and keyword analysis	The effects of both buyers and sellers on search advertising (sold to sellers, to appear in search results for buyers) as a revenue source over time	
Online Demand Under Limited Consumer Search	Kim, Albuquerque, and Bronnenberg	2010	Camcorders on Amazon	Yes	Somewhat (durable good)	N/A	Choice model	Creation and validation of a model	
Growing Two-Sided Networks by Advertising the User Base: A Field Experiment	Tucker and Zhang	2010	B2B services (similar to craigslist)	Yes	Unknown	N/A (clickstream data is of sellers, not purchasers)	Probit model	Sellers prefer to list their products in markets where many other sellers are operating, in order to increase the number of potential buyers	N = 3,314 sellers
On the Depth and Dynamics of Online Search Behavior	Johnson et al.	2004	Books, CDs, air travel	A mix of sites	Not complex (books, CDs), somewhat complex (air travel)	Multiple	Probabalistic models	Online search breadth is somewhat limited	N = 10,000
Modeling Online Browsing and Path Analysis Using Clickstream Data	Montgomery, Li, Srinivasan, and Liechty	2004	Online bookseller (Barnes and Noble)	No	Not complex	Mulitple	Dynamic Multinomial Probit Model	Understanding the path through web search is useful in predicting purchase conversion	N = 1,160

ESSAY 3

CURATION IN MARKETING: A FRAMEWORK[1]

[1] A version of this paper is being prepared with coauthor John Hulland for submission to *Spanish Journal of Marketing*.

Abstract

The word "curation" has escaped the art gallery and museum hall to find its way into common vernacular. Examples of online curation include assembling music playlists on Spotify and organizing themed collections of images on Pinterest. As online consumer curators are often using brands and product images, this activity is of interest to marketers. The actions taken by online consumer curators are similar to those of museum or art gallery curators: acquiring, selecting, organizing, and displaying content for an audience. The motivations for consumers to engage in online curation include building/displaying their identities and making social connections with their online audience. One outcome possible for the audience that views the curation is gaining access to carefully selected and recommended content. We discuss the possibility for firms to facilitate consumer curation by allowing their product images, for example, to be used as building blocks in consumer curations. Finally, we suggest several marketing-relevant propositions about this important and understudied area that can be addressed in future research.

The word “curation” has escaped the art gallery and museum hall to find its way into common vernacular. Examples of curation by consumers are easily found, especially in an online context, where consumers are carefully selecting and displaying content. For example, people can curate vacation photos on Instagram, a wish list of gift ideas on Pinterest, a selection of favorite mystery novels on Goodreads, and a playlist of road trip songs on Spotify. *The New York Times* states, “The word ‘curate,’ lofty and once rarely spoken outside exhibition corridors or British parishes, has become a fashionable code word among the aesthetically minded, who seem to paste it onto any activity that involves culling and selecting” (Williams 2009).

Curation previously referred to a specific function within the world of arts and museums. Perhaps the most famous curator in the contemporary art scene, Hans Ulrich Olbricht, explains that the profession of curator is tasked with preserving art history, selecting new art pieces, and making choices about arranging and displaying art (Jeffries and Groves 2014). Curation as it is defined today has much in common with the original meaning; curation refers to the act of “selecting, organizing, or presenting options (e.g., online content, merchandise, information, etc.), typically with the use of professional or expert knowledge” (Oxford Living Dictionaries 2019).

As the word has gained in popularity (see Figure 4.1 for Google search trends for “curate” since 2004), it has captured the attention of journalists, including the business press. Given the increased usage of the word, is raises the question of why curation, both as a term and an activity, is trending. For the most part, the rise in curation is attributed to the data overload that characterizes today’s world as a result of the internet. There is more information available online than any person would be able to sift through in his/her lifetime. Curation is a response to the overwhelming amount of content on the internet, sifting through what is available to find what is worthwhile. There are examples on social media, music streaming sites, and news sites of people helping to curate the internet for others in the face of an excess of digital content (Van Buskirk 2010).

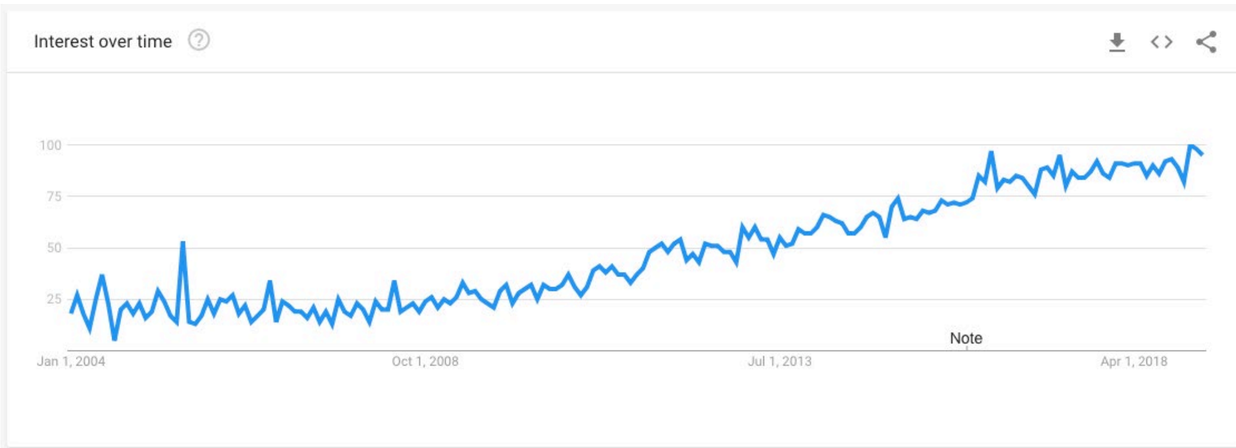

FIGURE 4.1

GOOGLE SEARCH WORLDWIDE TREND FOR "CURATE" (Google 2019)

Further, as a response to the vast amount of data available, much of the internet has become algorithmically-determined. Writer Ben Yagoda (2011) explains, "The Web [. . .] has developed in a such a way that raw data are sorted and organized not by human hands but by algorithms (number of page views, number of thumbs-up, Google's secret sauce, Wikipedia's universal access and veto power) that are certainly democratic and often useful, but just as often bring in too much noise and too much funk. 'Curating' the word and curating the phenomenon suggest a welcome recognition that some situations demand expert taste and judgment." Thus, curation is a response not only to the overwhelming amount of data, including product options and brands, available on the internet, but also to the algorithm-driven world that has taken over as a result of that data. Curation adds back a human touch, including subjective judgment, into a world that has become oversaturated (Bhaskar 2016a).

Despite the attention given to curation thus far in the press, very little academic research has addressed the topic. Some work has touched on the relevance and consequences of online curation activities for news/journalism (e.g., Villi, Moisander, and Joy 2012), and tourism (e.g., Miralbell, Alzua-Sorzabal, and Gerrikagoitia 2014).

Though curation is a broader phenomenon, consumers have an interesting and important role to play in curating content, including products and brands, online. The current paper focuses on curation activities that are relevant to marketers. As such, we are most concerned with curation related to products and brands, rather than other types of content (e.g., news). The precise definition of online consumer curation employed in our research is: to acquire, select, organize, and display one or more items of online content for an audience. This definition of online consumer curation is informed by both the classical definition of the term, used solely within the museum/arts world, and the expanded meaning of the term used in modern conversation.

In this conceptual paper, we introduce the phenomenon of online consumer curation as it relates to marketing by providing several relevant examples. Then, we outline the four-step process of online consumer curation (i.e., acquiring, selecting, organizing, and displaying content for an audience) and discuss motivations for consumers to engage in the activity, potential outcomes for the audience, and the role of firms as facilitators of curation. Propositions related to online consumer curation are provided in hopes of inspiring future research.

Examples of Online Consumer Curation

Though consumer curation can exist in the physical world (e.g., consumers assemble outfits and decorate their homes), we focus here on the digital world. Examples of online consumer creation abound. Much of this online consumer curation takes place on social media sites (e.g., Instagram, Pinterest), but it is not exclusively a social media phenomenon. In the following examples, consumers are actively curating images (both photography and online images), text, and audio files.

It is important to note that examples of consumer curation include both those who have a financial incentive to produce curated content (e.g., a sponsored post on Instagram) and consumers who curate for free. For some social media influencers and celebrities, it is possible to monetize their curation efforts, but we still consider this consumer curation, differentiated from firm curation (e.g., Zara's page on Pinterest).

On one thread on the online forum Reddit (https://www.reddit.com/r/EDC/), 196,000 subscribers share their "Everyday Carry" ("EDC") items, the essentials including pocketknives, pens, and wallets that they use daily (Reddit 2019). Users not only post a photo of their arranged assortment of items (i.e., curated displays), but also comment on one another's chosen items. This type of curation differs from other examples of online curation in that the consumers actually own the items that they curate. The EDC phenomenon exists outside of Reddit as well; on the website Flickr, a photography sharing website, one page devoted to EDC has close to 2,000 members (Flickr 2016). Figure 4.2 shows an example of one consumer's EDC on Reddit.

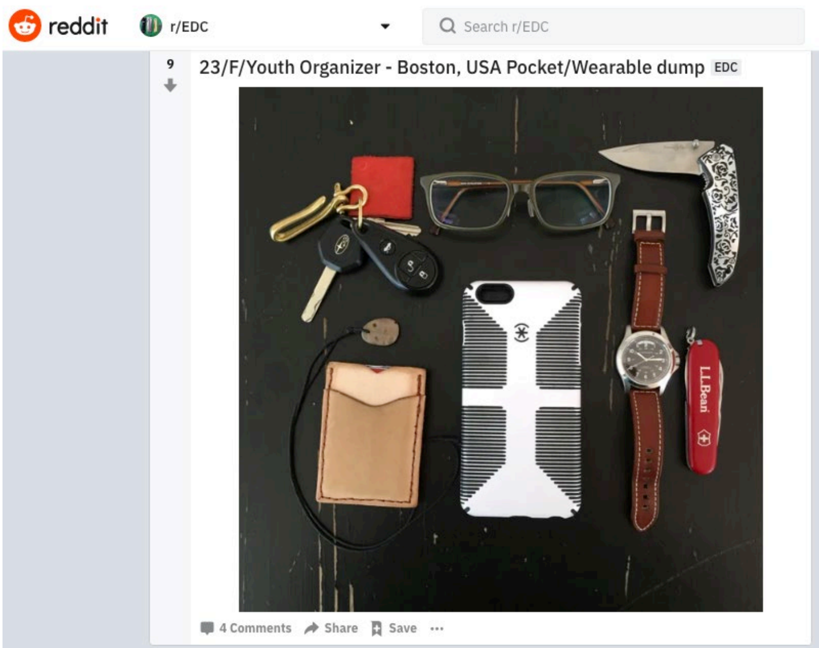

FIGURE 4.2

A CONSUMER'S CURATED "EVERYDAY CARRY" ITEMS ON REDDIT

The most popular curated-based social network site is Pinterest, which allows users to organize boards consisting of collections of "pins," typically photos or other images (Griffith 2015). Pinterest allows users to not only curate pins to serve personal organization purposes, but also to send social signals (Hall and Zarro 2012). The popularity of this site has inspired some social media research; for example, Lamberton and Stephen (2016, p. 160) highlight the "growing trend of consumers curating content in the form of product recommendations by using popular media sites such as Pinterest that make it easy to pull together information from across the Internet into a single place."

Regarding people's actions on Pinterest and similar websites, Zhong et al. (2013) state, "These users or content curators provide an editorial perspective by highlighting interesting content." Thus, consumers undertake curation efforts in order to assist fellow users of the website in uncovering useful or enjoyable content from the great amount of existing online content. Figure 4.3 shows an example of one board curated by popular blogger Joy Cho's; her account is the most popular on Pinterest, with 13 million followers (Oh Joy 2019).

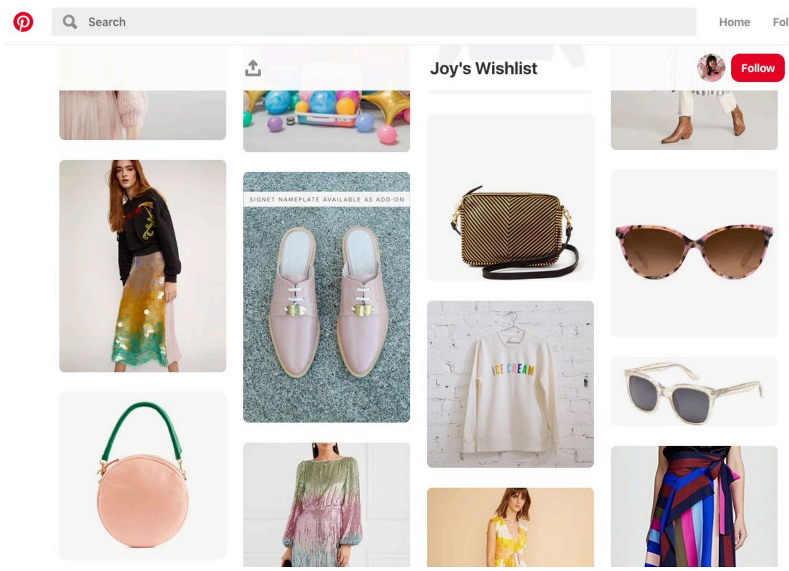

FIGURE 4.3

BLOGGER JOY CHO'S CURATED BOARD OF PINNED ITEMS ON PINTEREST

In addition to social media platforms (e.g., Reddit, Pinterest), one significant area where consumers are actively curating is on social shopping sites, websites that combine online shopping and social networking (e.g., Polyvore, Fancy, Wanelo). On such sites, consumers are often able to select and organize (i.e., curate) fashion products into themed lists/boards, interact with one another's curated content (e.g., providing likes or comments), and either purchase directly on the site or "click-through" to purchase from a retail partner. The phenomenon of "social shopping" sites has been ongoing since the mid-2000s (Tedeschi 2006). Not a uniquely Western phenomenon, consumers across the world are active on social shopping sites (e.g., LimeRoad in India). In 2014, the top 500 retailers earned $3.3 billion from social shopping, a figure that is likely to increase (Smith, 2015). Further, the reach of consumer-curated displays extends beyond the specific social shopping sites as curated lists/boards can also be shared on other social media sites. Some research has addressed consumer activity on social shopping sites. For example, Olbrich and Holsing (2011) find that curated fashion collages (called by these researchers "styles") enhance consumer browsing behaviors on a social shopping site. Figure 4.4 shows examples of curated fashion displays posted to a group's page on Polyvore.com.

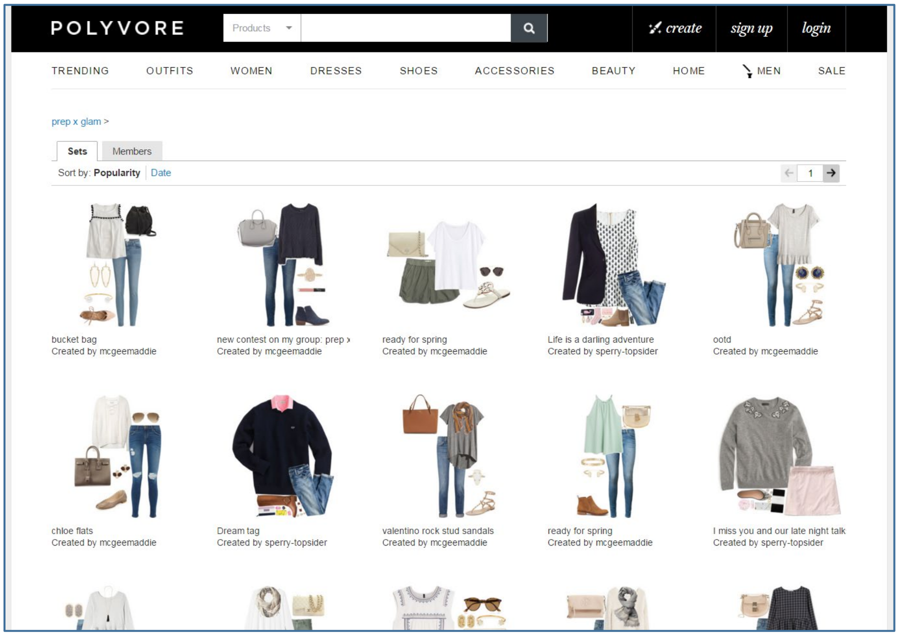

FIGURE 4.4

A CURATED FASHION COLLAGE POSTED TO A GROUP'S PAGE ON POLYVORE

Not only are consumers curating products, but they are also curating other types of digital content, including music. Spotify is a streaming music application with 170 million monthly active users and 75 million paying subscribers (Spotify 2018). One important feature on Spotify is user-curated playlists, of which there are over 2 billion (Popper 2015). Figure 4.5 shows an example of user-created playlist; this example comes from user "Yoga Girl," who curates monthly playlists intended as background music for yoga practice and has about 174,000 followers on Spotify.

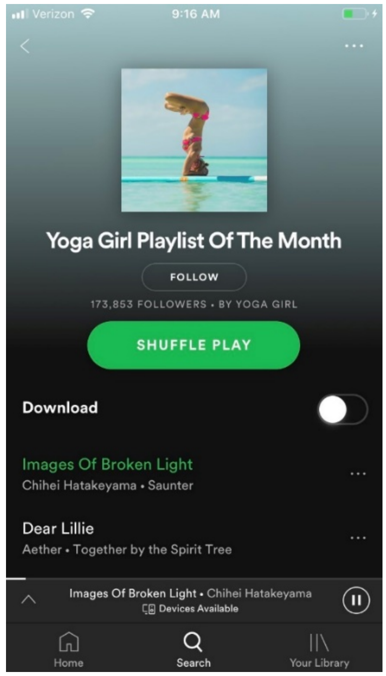

FIGURE 4.5

A CURATED PLAYLIST BY YOGA GIRL ON SPOTIFY

A Consumer Curation Framework

The four steps of consumer curation are: acquiring, selecting, organizing, and displaying content for an audience, as shown in Figure 4.6. This framework addresses static curation, that is, curated displays that are posted online and remain the same. Certainly, other types of dynamic consumer curation exist and can be studied in additional research. First, a consumer acquires the content to be curated from different places on the internet. Then, he/she carefully selects the precise pieces of content that will be curated. The consumer is then tasked with organizing the content into an assembled grouping. Finally, the curated content is displayed for an audience, either real or implied.

Curators are different from creators. In the same way that art curators select and display pieces of art created by others in a gallery, online consumer curators assemble content created by others (Cairns and Birchall 2013). Though curation can certainly be a creative act, curation differs from creation. The two activities are closely related, but typically, curators did not create the content that they are curating. Thus, curation, including online consumer curation, is about adding qualitative judgment to the careful selecting and arranging of content created by others. Artist Brad Troemel (qtd in Blight 2013) explains that digital curating is "any act where a person organizes visual content on the internet in a way that creates meaning through the differences and similarities of their collected images." Thus, there is information portrayed through the act of curation (e.g., a demonstration of the curator's style or taste).

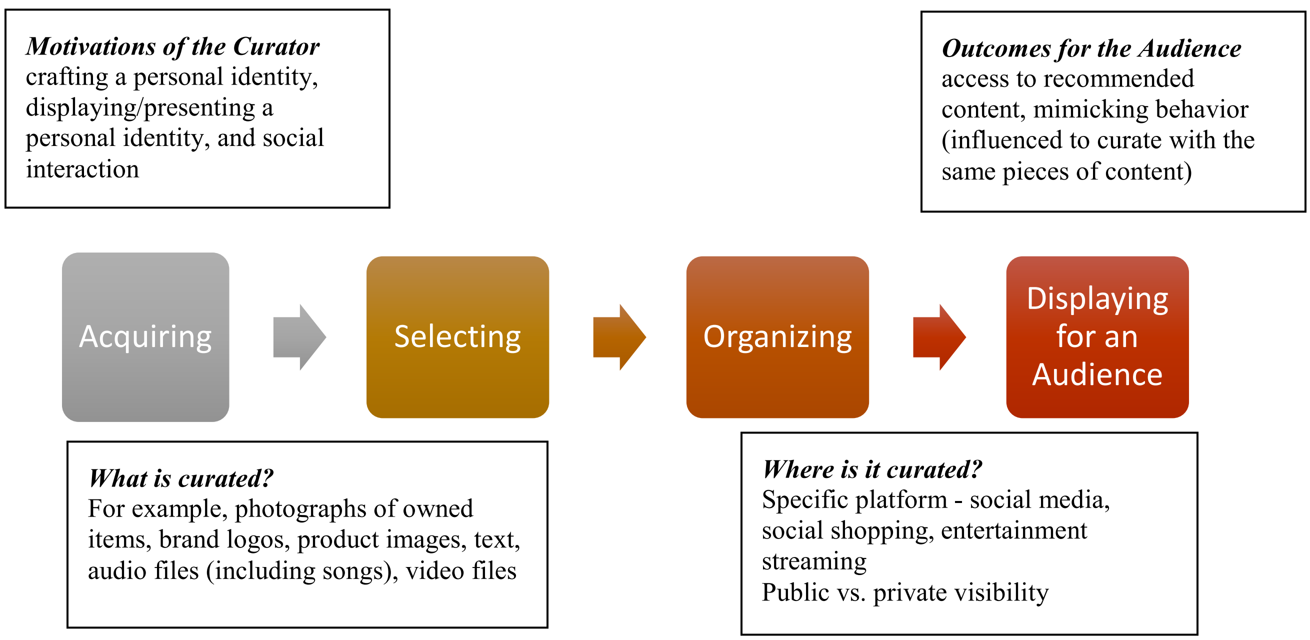

FIGURE 4.6

THE FOUR STEPS OF ONLINE CONSUMER CURATION

Acquiring

Though consumers have a greater ability to curate online than ever before, the behavior of consumer curation, beginning with the step of acquisition, is not a new phenomenon. In fact, the precursor to the modern museum, the original home of the curator, is "kunst- und wunderkammer," (cabinet of art and marvels), a display of thoughtfully gathered and arranged curiosities. Such cabinets were popular in the homes of European people in the sixteenth and seventeenth centuries, in order to display their acquisitions from the worlds of art, nature, and science (Koeppe 2002). In the same way that people in the past obtained unique articles for display in their homes, people today have the ability to carefully select and display the objects, entertainment, and general content that surrounds their lives. “The urge to curate is a profoundly human one. [. . .] Collecting and displaying possessions shows that we still like to hunt and gather that missing piece, just like our ancestors” (Rose 2013).

Online, consumers can either curate items they actual own (in a photograph, for example) or online images of products that they do not own. In examples of consumers curating their owned items (e.g., EDC on Reddit, see Image 1), it is interesting to note that this four step process begins with purchase, rather than ending with purchase as an outcome, as is the case in many consumer behavior models. For other types of online curation in which the items are not necessarily actually owned by the consumer, he/she may gather content from many different places online. For example, on Pinterest, one can curate with items that have been used by others on the site, or pull in images from elsewhere on the internet (e.g., retailer’s websites).

This first step of curation has some aspects in common with collecting behavior (e.g., collecting art or coins), though it differs in several important ways. In both collecting and curating, consumers may be concerned acquiring items, perhaps as a reflection of their identities or taste. Some research has begun to differentiate curating from collecting. Min (2017) contrasts curating versus collecting physical items and finds that curators have different acquisition and display goals, relative to collectors.

Selecting

The items that were acquired in the first step are then carefully sifted through as the consumer selects the ones chosen to move forward in the curation process. In doing so, this selection process reflects a consumer's qualitative taste or judgment as he/she chooses specific items (Rosenbaum 2011, Bhaskar 2016b). "The job of a content curator is not to create more content, but to make sense of the best and most relevant content and thereby to add a voice and point of view above existing material" (Villi, Moisander, and Joy 2012, p. 491). Thus, in the step of selection, the consumer is employing his/her subjective judgment in order to choose items, which then reflect his/her taste and skill at curation.

The steps of acquiring and selecting are both concerned with *what* the consumer is curating. Online, examples can be found of consumers curating all types of digital content: photographs of their owned items, brand images, product images, text, audio files (including songs), and video files. Consumers are actively displaying items they have purchased (e.g., Reddit EDC), curating items they wish to own (e.g., Pinterest "wish list"), and also arranging digital content for the benefit of others (e.g., Spotify playlist for a yoga class).

Organizing

Once the pieces of content have been selected, the consumer must organize them into an assembly. In addition to the acquisition and selection steps, in which a consumer can demonstrate his/her taste, the consumer can also portray creativity in assembling the content. For example, on Polyvore, consumers show a lot of creativity in the way they arrange the curated outfits, sometimes even including text (e.g., an inspirational quote), images (e.g., celebrity), or other non-fashion accessories for the outfit (e.g., Starbucks bottled Frappuccino).

By assembling items together in the creation of a display, consumers are creating associations among the pieces of content that they curate, including brands. Referencing consumers' posting activities on their personal websites, Schau and Gilly (2003, p. 400) explain, "Digital consumers can activate a type of cobranding, commingling brand logos, and creating relationships between brands." Juxtaposing brands in this way can be consequential. For example, in an article in *Harper's Bazaar*, Jenna Lyons, the previous president of J. Crew notes, "Yves Saint Laurent is more interesting if it's paired with J. Crew or H&M. Because everyone is sort of homogenized these days, adding that stuff makes someone interesting" (Wolfe 2008).

Displaying

The outcome of curation is a display of some kind that is visible to either real or implied others, though displays can differ in terms of how publicly they are presented. Consistent with the original museum context of the activity of "curation," the outcome of curation efforts by online consumers can also be termed a "display." Museum curators are charged with arranging and organizing displays in order to connect with and inform visitors to the museum. In the same way, curating consumers spend time and energy to create displays for the possibility of benefitting or influencing an audience, which is the implicit goal of curation.

Both organizing and displaying, the two final steps in the consumer curation process, are concerned with *where* the curation will take place. A consumer must decide if he/she wants to post on a public website (e.g, Reddit), or on a private account on social media (e.g., Instagram account set to private so only his/her approved followers will see it). Interestingly, the size of the audience can impact what a person would choose to share. Barasch and Berger (2014) find that consumers broadcasting to a large audience are more likely to act in self-preservational ways, sharing content that makes them look good.

Motivation

The above four-step consumer curation process begs the question, *why* do consumers engage in curation behavior? As mentioned, some consumers monetize their efforts (e.g., social media influencers who are paid by company to promote products), but most consumers are performing this curatorial work for free. Thus, what utility are consumers receiving from spending their time and energy to curate?

Research into similar online activities to curation (e.g., engaging in WOM online, posting on personal websites) and research into peoples' relationships with branded content point to three main motivations for consumers to curate online: crafting a personal identity, displaying/presenting a personal identity, and social interaction.

People carefully choose to surround themselves with objects, including digital content, to craft and reflect their identities. In particular, the importance of consumers' relationships with brands to their identities has been studied in depth by marketing researchers (e.g., Fournier 1998; Ahuvia 2005). Escalas and Bettman (2005, p. 379) explain that meaning transfers from goods to consumers as they "construct themselves through their brand choices." Belk asserts that issues of identity are essential in understanding consumption, and that one's possessions can become part of the definition of one's self (1988). Belk (1988, p. 160) states, "It seems an inescapable fact of modern life that we learn, define, and remind ourselves of who we are by our possessions." In this way, one's identity is constructed through the curation of particular products or brands. Similarly, one of the founders of Polyvore, Pasha Sadri, explained that curating an outfit is highly integrated with a consumer's identity (Jacobs 2010).

Because curating is about using one's qualitative judgment, it communicates something about the curator's personal or social identity. Thus, the literature on self-presentation (Goffman 1959) and the construct of the extended self (Belk 1988) is foundational to understanding curation behavior. In an update to the idea of the extended self released for the digital age, Belk (2013) re-affirms the importance of the extended self construct in modern times; for example, the ability of consumers to publish their music playlists online turns the private act of acquiring music into a public act. Belk (2013, p. 479) invokes Goffman's presentation of self in stating, "the ability to publish our playlists online can say a great deal more about us than opening the windows and cranking up our stereo." Indeed, people have the ability to publically express their identities to a wider online audience than ever before. Schau and Gilly (2003) also invoke the literature on self-presentation in their study of the motivations for creating and maintaining personal websites. Thus, it has been established that online activities can be motivated by the desire to display one's identity.

Finally, because of the inherent social aspects of curation (displays are intended for an audience), social connection is a final important motivator for consumers to engage in curation. We can turn to research on online word-of-mouth (eWOM) to understand the social drivers at work in curation. For example, among the main motivations for participating in eWOM behavior, Hennig-Thurau et al. (2004, p. 39) find "consumers' desire for social interaction" to be important drivers. In a study of content providers on a site like Twitter, who do not gain financially from their efforts, researchers contrasted two potential motivators: intrinsic utility, inherent enjoyment of doing the activity, or image-related utility, being motivated by others' perceptions of the activity, akin to status seeking (Toubia and Stephen 2013). Toubia and Stephen (2013) find that noncommercial users of Twitter are more likely driven by image-related utility. These results likely generalize to online consumer curation activities as well.

Outcome

The outcome of a consumer curation as it connects with its audience may take two main forms: serving as a recommendation for others to consume the same curated content, and influencing others to also curate with the same pieces of content. For example, an influential display of curated songs (e.g., a public Spotify playlist) may lead to a viewer's approval/enjoyment of the curated content (i.e., listening to it themselves), or the viewer's mimicking behavior (i.e., employing the same songs or artists in their own public playlists). Thus, online curation serves as a kind of content or product recommendation. Villi, Moisander, and Joy (2012, p. 492) explain, "Curators are knowledge brokers that interpret, publicize and endorse content. Thus, there is always an aspect of recommendation involved."

These outcomes raise the question of why an audience would want to view curations. Holt explains that, due to time and energy constraints, consumers are turning to "cultural infomediaries," noting that "Consumers want to author their lives, but they increasingly are looking for ghostwriters to help them out" (2002, p. 87). People want access to the best content, from the overwhelming number of options available, and may seek curations in order to uncover it. As mentioned previously, much of the internet, including product recommendations on retailers like Amazon.com, for example, is driven by algorithms. Researchers have found that exploring links (e.g., YouTube videos) recommended by a person's social network lead to more efficient and enjoyable search process, rather than just following algorithmically-induced recommended links (Goldenberg, Oestreicher-Singer, and Reichman 2012). Thus, the human aspect of curation can be important as well.

The Role of Firms in Consumer Curation

Within the realm of consumer curation, firms can play an important role as facilitators and providers of content, akin to the artists whose work is chosen and displayed by a curator in an art gallery.

The act of curation may play a role for some consumers in crafting and displaying their identities. Several researchers note that it is becoming increasingly important for marketers to recognize their role in facilitating consumers' "identity projects," a term often used by researchers in discussing the construction of personal and social identities. Holt (2002, p. 87) states, "Consumers will look for brands to contribute directly to their identity projects by providing original and relevant cultural materials with which to work." Similarly, in explaining how marketers can best operate in the new interactive marketing paradigm, Deighton and Kornfeld (2009, p. 9) state, "The form of interactivity most attractive to marketing is that which can facilitate peoples' identity projects and contribute to the collective making of meaning."

Within the world of consumer curation, we can see the use of brands and products as building blocks to build or reflect a consumer's identity when they are used in curations. In this way, firms offer themselves as facilitators for curating consumers. One example of firms being helpful facilitators of consumer curation can be found on social shopping sites, where firms can not only upload images to the platform of their items to be used by curators, but can also try to engage consumers. For example, brands can hold contents that encourage consumers to curate using their item images. One example of this is the brand Coach, which sponsored a curation contest on Polyvore. There were 3,692 entries into the contest that garnered over 100,000 "likes" (Corcoran 2010).

Propositions for Research into Consumer Curation

Above, we outlined the four-step framework consumer curation, as well as motivations of the curator, outcomes for the audience, and the role of firms as facilitators. The following propositions are focused on the relevance for marketers. Given the limited research into curation in marketing and the growing importance of this phenomenon, we propose several areas worthy of further inquiry:

- One very interesting way in which the use of brands online differs from "real life" use is that consumers have no financial or physical constraints in using brands to express themselves. Though consumers can curate items they actually own, they are not constrained to only these items, giving them "greater freedom to express their identities through digital association rather than ownership or proximity" (Schau and Gilly 2003, p. 387). The fact that consumers can use brands that they do not currently own to express themselves should be of interest to marketers. Perhaps it is the case that curating a brand that one does not own reflects a consumer's aspiration to an "ideal" self that would like own the brand. By identifying these consumers, marketers could uncover a precise list of their customers-in-waiting.
- Firms may also be able to uncover consumer preferences for particular products from online consumer curation. The fashion brand Diane von Furstenberg used consumer behavior information from contest they sponsored on the social shopping site Polyvore to identify the items with the most potential to be popular in the upcoming season. "An opal platform shoe was used more often than any other item in the line, so the company ordered more of it, figuring demand at retail would be strong" (Corcoran 2010). Research should address how closely online consumer curation maps onto product purchases, in order to provide direction for firms hoping to use this metric. This would add to the literature on tying social media activities to actual purchases (e.g., Yadav et al. 2013).

- Research should address the possibility that curating consumers may have a higher level of brand engagement with the brands they employ in their curations, one of the many positive outcomes of interest to firms. Olbrich and Holsing (2011) suggest that such activities can build brand awareness and product loyalty. As curation activity is a behavioral metric, visible to firms, it would be possible to then gauge attitudinal measures by this visible behavior.
- In addition to studying the impact of curation behavior on the curator him/herself, research should address the true impact of curated displays on the audiences that view them. The motivation for curation also includes influencing others in presenting *themselves* with products or brands, inciting mimicking behavior. Thus, the ways in which consumers are curating displays may affect not only the curator him/herself but also the viewer of the curated display.
- We suggest that one way for firms to bring value to consumers (and can also benefit the firm) is by helping facilitate curation. However, much remains to be discovered regarding how firms can be appropriate and efficient facilitators of curation, especially operating in social media spaces, where much of the curation activity is taking place. Firms should move forward with the caveat from Fournier and Avery (2011, p. 193) that firms must understand that "social media was made for people, not for brands."
- Inherent in the activity of curation is the combination of brands into a single display, rather than offering a standalone opinion on a brand, as is the case with other types of UGC (e.g., Twitter tweets and YouTube product reviews). Knowing the other brands and products alongside which the focal brand is often being curated should be of interest to marketers. Marketers desire a tight control over their brand image (Park, Jaworski, and MacInnis 1986), which can certainly be affected by the ways in which is being used in consumers' curation

activities. This type of research would also add nuance to the UGC literature, as consumer curation offers a different lens through which to view the potential impact of UGC when it includes more than one focal brand/product.

- The interesting phenomenon of curation offers an area of study that is not only interesting theoretically and for its importance to practitioners, but also because of the opportunity to utilize novel research techniques. Curation-based social media sites are an example of rich media formats (video, images) and represent the next wave of social media and social media research. Lots of prior research has studied text-based social media sites and WOM, but due to the difficulty in analyzing such rich information, less work has focused on rich media formats. As more sophisticated analysis techniques become available and used by marketing researchers for analyzing this type of information, online curation will offer a rich domain to be studied.

Conclusion

Curation as both an activity and a word is everywhere. Interestingly, the proliferation of the word "curation" has lead to many commentators bemoaning the use (and perhaps over-use) of the word. On NPR, Scott Simon (2012) explains, "In recent years, the word 'curate' has been plucked out of museums and pasted onto everything from cosmetics, furniture and fashion lines to recipes, music- and photo-sharing websites and cat videos." A writer on the home style website Apartment Therapy promised her readers to stop labeling things as "well-curated" so often, at their request (Brenner 2015). The use of the word "curation" outside of its original meaning has also stirred up lots of discussion in the art/museum world about the professional function of the role (e.g., Balzer 2014, Cairns and Birchall 2013). However, as long as people face an overwhelming amount of information, product options, and online content, the role of the curator will remain vital. As Rosenbaum (2014) writes in defense of the word "curate," "The firehose of unfiltered information that's masquerading as content demands a quality curation filter." Consumers certainly have a role to play in helping one another by uncovering the best online content. The phenomenon of online consumer curation is very relevant for firms and represents an interesting an understudied area of modern marketing.

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CHAPTER 5

CONCLUSION

Within the realm of online firm-consumer interactions, I address two main themes that characterize my research: curation and platform firms. Given the opportunity that firms have to provide value to consumers and benefit from these two areas, they are worthy of study in the marketing literature.

Curation

Essay 3 (Chapter 4) examined online consumer curation, presenting a conceptual framework for understanding this phenomenon. Though consumer curation is characterized by consumer-to-consumer interactions, this activity has consequences for marketers, as online consumer curators are often using brands and product images. Actions taken by online consumer curators are similar to those of museum or art gallery curators: acquiring, selecting, organizing, and displaying content for an audience. Consumers can be motivated to engage in online curation because it allows them to build/display their identities and to make social connections with their online audience. Audiences of curated content are motivated to seek out such content because it allows them to uncover selected and recommended items. Firms play a role in consumer curation by allowing their product images, thus being the building blocks used by consumers in their curated collections.

Essay 1 (Chapter 2) examines another type of curation, where firms act as active curators. Curation is a popular and growing business model, but little research has been undertaken to provide direction to curating firms about how they can best undertaken this activity. Within the context of firm curation (e.g., subscription boxes, recommended entertainment streaming), one main tension is whether a human or an algorithm is portrayed as the mastermind behind the product/content selection. Managers may believe that humanizing the curator, especially in cases where algorithmic decision-making is relied upon, is necessary to make consumers more comfortable. However, I find that not only may firms not face a negative reaction to revealing algorithmic decision-making, but they may, in fact, suffer a negative impact from over-humanizing the decision maker. This preference for algorithms over humans operates through the mechanism of capability; consumers believer that algorithms are better than humans at handling complex choice option sets. Thus, especially in the case of curated services that pull from expansive catalogs of items or make very complex choices, the firms should be encouraged to convey to consumers their reliance on algorithmic decision-making.

Platform Firms

Essay 2 (Chapter 3) examined the insights that can be drawn from aggregate consumer search data for the benefit of online platform firms, firms that link buyers and sellers on the internet. From specific consumer actions on the website, it is possible for the platform firm to gauge how close the consumer is to ceasing their search process and making a purchase choice. From that understanding, the platform firm or its salesperson representative can make appropriate nudges to the consumers, either to offer assistance as the search process continues or help the consumer make a final purchase choice.

I find that engaging in three particular types of search actions are consistent positive signifiers of purchase – reducing the consideration set, search depth (minutes spent searching), and investing time in exploring experience attributes. If the platform firm sees these types of actions being undertaken by consumers, it is likely that he/she will be purchasing soon. I also find that when the consumer is engaging in these three actions – search breadth (number of options considered), exploring search attributes, and increasing the consideration set – the customer likely to continue searching beyond that browser search session. That is, the consumer might be in need of a salesperson's assistance in the ongoing search process. These types of nudges from the salesperson, based on the consumer's active search behavior, could help bring efficiency to the search and purchase process.

The empirical context explored in this research is a very complex product, an apartment lease, which can differ greatly among many different dimensions (e.g., price, location, features, and layout). Thus, the results of my analysis should extend to other highly differentiated products for which a consumer might invest a lot of time searching (e.g., cars, appliances, travel-related purchases, financial investments).

Future Research

It is clear that there remains much to be learned within the exciting research areas of curation and platform firms. These areas are important ways in which firms can assist consumers in their decision-making, especially in a world characterized by massive amounts of data. Specifically, future research ideas can be generated from each of my three essays.

Essay 1: When Humanization Backfires: Consumer Preference for Algorithmic Product Curation

As technology increases and algorithms assist more consumer decisions, the relationship that people have with algorithmic decision-making will be of increasing importance. In Essay 1, I examine algorithmic versus human decision-making in very relevant but relatively low-stakes consumer decision contexts (e.g., curated music playlists). However, there are real-world examples of when a consumer must choose between algorithm and human advice in contexts with higher risk to the consumer (e.g., algorithmic advice on financial services like selection of a mutual fund). Thus, it would be interesting for further research to investigate higher-risk consumer scenarios. Given the results of my research, which finds that consumers are more comfortable having algorithms make decisions in complex choice contexts than humans, I would expect consumers to have an even stronger preference for algorithms in contexts of higher risk.

It is likely that some consumers have had the opportunity to become comfortable with recommender algorithms in certain domains, like entertainment streaming sites and online retailers that provide automated product/content recommendations. However, as algorithmic decision-making and advice becomes more commonplace in the mrket, there may be opportunities to study areas relevant to consumers in which they have not yet been exposed to algorithmic decision-making.

Essay 2: Insights for Online Platform Firms from Sequential Consumer Search

Essay 2 utilized site-centric clickstream data, the record of consumers' "clicks" on one focal website. Given that one platform firm provided the data used to generate the results in Essay 1, it would be useful to compare these results to data from other firms. The main drawback from this type of site-centric clickstream data is the lack of information from consumer's search activity on other websites; data that allows searching consumers to be traced across different websites would be useful to study as well.

My work suggests to the platform firm that it is possible to make interventions, signaled by specific consumer actions, that would increase search and purchase efficacy. Thus, the logical next step for this research is to validate these suggestions through a field experiment. Doing so would also allow for answers to the following questions to be found: Is there an ideal number of times for the platform firm to intervene? Does intervention actually lead to more efficient search and purchase process? Are consumers more or less satisfied with their final purchase choice when the platform firm has assisted their search process? Much remains to be researched in this interesting research domain of active, rather than passive, platform firms.

Essay 3: Curation in Marketing: A Framework

After introducing the phenomenon of consumer curation, I outlined several propositions to inspire future research. For example, research could address the difference in the use of brands that consumers do and do not actually own in their online curations. One interesting way that curating brands online differs from "real life" use is that consumers have no financial or physical constraints in using brands to express themselves. Consumers may curate a brand that they do not own in order to reflect their "ideal" self that would like to own the brand. By identifying these consumers, marketers could expose a precise list of their customers-in-waiting.

Increasingly, researchers are try to tie online consumer actions, including leaving reviews, engaging in eWOM, and searching for products, to actual purchase metrics. Within the realm of curation, this may be possible as well. For example, firms may also be able to uncover consumer preferences for particular products from online consumer curation. If a particular product is used frequently in consumer curation, it could signal increased demand for that product. Research should address how closely online consumer curation maps onto product purchases, in order to provide direction for firms hoping to use this metric.

Consumers create user-generated content surrounding products and brands online in ways that have been studied by researchers (e.g., Twitter tweets and product reviews on YouTube). However, what is different about curation is that inherent in the activity of curation is the combination of brands into a single display, rather than offering a standalone opinion on a brand. The co-branding literature may be relevant here, as consumers are exposing or creating associations between brands by combining them together into one display. Knowing the other brands and products alongside which the focal brand is often being curated should be of interest to marketers. The study of curation, under the umbrella of UGC research, will help to expand knowledge in this area, since it is more focused on the combination of products/brands than recommendations or options on one focal product/brand.

Taken together, the three essays that comprise this dissertation show that firms can serve an important role in assisting consumers in their decision-making. Doing so can bring value not only to consumers, but also to the firm itself.