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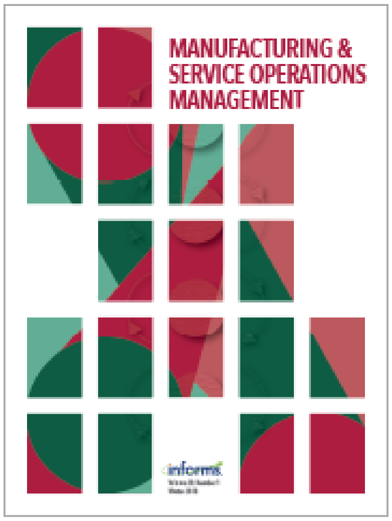

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Choice Overload and the Long Tail: Consideration Sets and Purchases in Online Platforms

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Abstract. ***Problem definition*:** This paper examines frictions in the shopping funnel using empirical clickstream data from an online travel platform. We analyze (a) customers' heterogeneous search and purchase behaviors and (b) their reactions to changes in assortment size. We then develop a consider-then-choose model to generalize our findings. ***Methodology/results*:** We characterize the online customer journey as a two-stage consider-then-choose framework. In the consider stage, we analyze the consideration set formation and show that heterogeneity—familiarity with the assortment—amplifies the number of options; in the purchase stage, it drives preferences for niche versus popular choices. A real-world high-stakes field experiment reveals that shrinking the menu produces mixed results: highlighting the market for the long-tail for some customers and reflecting choice overload for others. Finally, we build a psychologically rich consider-then-choose model with (a) heterogeneous preferences for product features and (b) heterogeneous search costs moderated by search fatigue, theoretically characterizing the impact on consideration sets and conversion rates. ***Managerial implications*:** Identifying frictions in the shopping funnel is critical for online platforms, especially when pain points hurt click-through or conversion rates. Which options matter to which users? What is the right assortment size? Although online platforms can offer virtually unlimited assortments, managers may assume frictionless environments—which is not always the case. Our findings offer insights into improving the customer journey by considering heterogeneous preferences and boundedly rational heuristics.

Supplemental Material: The online appendices are available at https://doi.org/10.1287/msom.2021.0318.

Keywords: OM-marketing interface • empirical research • consumer behavior • experiments

1. Introduction

"People don't know what they want until you show it to them."

—Steve Jobs, co-founder of Apple

Online platforms have always been increasing the assortment variety. Also, in many cases, the number of options can be overwhelming. Despegar.com offers more than 500 hotels in Sao Paulo, Brazil; Zara offers 11,000 items on a single day (Martinez-de Albeniz et al. 2024); the number of listings in New York City (NYC) on Airbnb went from 2,600 in 2010 to more than 16,400 in 2014 (New York State Attorney General 2014); JD.com increased the number of items from 1.5 million in 2011 to 40.2 million in 2014 (SEC 2014); and there are 500 million distinct grocery items on Instacart's catalog (Instacart 2022). Indeed, when Fidji Simo was appointed as chief executive officer (CEO) of Instacart, she said that customers expect "the widest selection of food at their fingertips" (Instacart 2021).

In principle, the idea that offering more choices should always be better is fairly intuitive: the larger the assortment, the higher the likelihood the consumer will find the preferred variety (Baumol and Ide 1956). However, recent studies on search costs and assortment design (Wang and Sahin 2018, Liu et al. 2019, Li and Netessine 2020), consumer behavior in marketing (Iyengar and Lepper 2000, Schwartz 2004), and behavioral operations (Chen et al. 2020, Donohue et al. 2020) question the benefits of an ever-increasing assortment and reveal shopping frictions. Most studies in operations management have theoretically examined the interplay between search costs and purchase decisions. Thus, contributing empirical evidence to this debate, especially in the context of online platforms, is important for both scholars and practitioners.

Although it is tempting to quickly speculate about the benefits and drawbacks of a platform's variety, it is crucial to examine this question through the lens of the customer journey. How do customers screen options?

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What options are purchased? Can there be too many options? The customer journey in online platforms can be analyzed as a *consider-then-choose* journey: consumers first form a consideration set from the assortment offered to them, and after examining the consideration set, they make a purchase decision. Conceptually, two-stage models are suited to characterize complex decisions because (a) consumers are confronted with many options, and (b) each option has many unknown attributes (Mehta et al. 2003, Gilbride and Allenby 2004, Hauser et al. 2010, Van Nierop et al. 2010, De los Santos et al. 2012, Wang and Sahin 2018).

These aspects hold particular relevance for business-to-consumers (B2C) online platforms: restaurants (TheFork, OpenTable), food delivery (Grubhub, Glovo), experiences (TripAdvisor), short-term rentals (Airbnb), hotels (Expedia), fashion (Amazon), and furniture (Wayfair). For example, when customers enter a destination city and target dates, they are presented with hundreds of available hotel options in the search results. Furthermore, the thumbnail of each individual option contains fuzzy information—for example, overall score (but not the reviews), neighborhood (but not the address), and stars (but not the amenities)—making the selection process both challenging and tiring. Customers may be unfamiliar with the city, have concerns about public transportation, or may want to know guests' opinions about breakfast, cleanliness, and hotel and urban amenities.

Our work contributes to the literature by combining empirical data sets and a theoretical model to study three problems: search costs and the formation of consideration sets, preferences for niche versus popular choices, and changes in the online assortment size. Our empirical strategy utilizes clickstream data sets and a field experiment in collaboration with the leading online travel platform Despegar. The setting is hotel bookings, covering more than 320,000 users, 601,000 searches, and 18,000 transactions. Moreover, the expenditures are economically meaningful: The average transaction is more than $250 dollars.

We begin our paper by empirically analyzing the formation of consideration sets. We leverage customer heterogeneity and show that customers with high familiarity with the menu tend to form larger consideration sets. This novel familiarity effect connects to behavioral studies showing that familiarity can moderate cognitive information processing costs and drive consumers' variety breadth preferences (Park and Lessig 1981, Alba and Hutchinson 1987, Prelec et al. 1997, Coupey et al. 1998, Mogilner et al. 2008). Next, we show that familiarity explains relative preferences for niche hotels versus best-seller hotels. We also utilize web-scraping data to show that niche options have narrow-appeal features, such as fewer reviews (but not worse quality) and greater distance from touristic spots in the city. These set of results reinforce the value of the long tail in online assortments (Brynjolfsson et al. 2011, Gallino et al. 2017, Donnelly et al. 2023).

We move on to investigate how consumers respond to changes in the size of the choice set. We implement a novel field experiment at the consumer level in a high-stakes, real-world context. The design of the experiment is as follows: For any user searching hotels in three destinations, the user was either shown the full list of options (control) or fewer options (treatment). Then, user-level data allowed us to track and analyze click and purchase behaviors. We find that, although all consumers form a slightly smaller consideration set when they are presented with a smaller assortment, low-familiarity customers exhibit a higher purchase probability and high-familiarity customers exhibit a lower purchase probability.

Critically, that purchases increase when the choice set is reduced reflects a behavior often referred to as *choice overload*. Although, to the best of the authors' knowledge, choice overload in a high-stakes online shopping environment has not been documented, it connects to an extensive literature using laboratory experiments and supermarket field experiments (Scheibehenne et al. 2010, Chernev et al. 2015).

Finally, we introduce a psychologically rich theoretical model to generalize our understanding of shopping frictions in B2C online platforms. Our model follows the consider-then-choose paradigms (Hauser and Wernerfelt 1990, De los Santos et al. 2012, Wang and Sahin 2018), but with two distinctions. First, when evaluating the consideration set, the per-unit search costs incurred are not fixed but (a) heterogeneous across customer segments and (b) a general function of the assortment size. These capture that, although any kind of heterogeneity (e.g., familiarity, expertise, purchase frequency) can attenuate search costs, the cognitive effort of processing an assortment is not negligible. Said differently, thinking about alternatives increases the "information load" (Scammon 1977)—leading to cumulative effort and fatigue. In particular, the cognitive burden from forming the expected utility over all the products in the assortment carries over to the choose (evaluation) stage, with this fatigue being exacerbated by the sheer number of options. Second, we incorporate customers' heterogeneous preferences for product attributes.

Our framework enables us to characterize the shopping journey, from consideration set formation to purchase decision, taking into account the presence of behavioral frictions. We further develop generalizable insights by conducting numerical simulations for various rates of assortment reductions across the parameter space, including situations where platforms either obfuscate or are transparent about product attributes.

Taking a step back from our specific online setting, our results deepen our understanding of consumer

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behavior in operations management in at least two ways. First, we shed light on the role of customer heterogeneity in search costs during the formation of consideration sets, as well as on preferences for niche versus best-seller options. Second, our findings indicate that platforms can extract additional gains by customizing the size and variety of their assortments. These insights are surprising because one might assume that online environments, with their virtually infinite options, would reduce the frictions present in brick-and-mortar stores, which are constrained by limited shelf space and physical navigation through aisles. Our managerial implications underscore the value of leveraging customer heterogeneity rather than relying on one-size-fits-all heuristics. Ultimately, both "less is more" and "more is more" can be true.

In Section 2, we review the related literature. We then describe our data sets and the experiment design in Section 3. In Sections 4–6, we develop and empirically test hypotheses about customers' browsing and purchasing behaviors. In Section 7, we develop a theoretical model. Finally, we conclude in Section 8.

2. Related Literature

Our research contributes to two streams of literature: (a) assortment variety and consumer behavior and (b) formation of consideration sets.

2.1. Assortment Variety

The effects of expanding or reducing assortment variety remains a popular question of interest, especially in marketing and operations management. The early studies of Dreze et al. (1994) and Boatwright and Nunes (2001) show that sales increase after reducing the number of low-selling stock-keeping unit in grocery categories. However, Borle et al. (2005) and Sloot et al. (2006) document that removing low-selling items and brands resulted in lower purchase frequency and purchase amounts. Li and Netessine (2020) shows, in an online peer-to-peer holiday property rental platform, that doubling the market size substantially reduces consumer confirmation rate and host occupancy rate. Other studies indicate that the assortment size also affects perceived variety and store choice (Broniarczyk et al. 1998, Hoch et al. 1999, Berger et al. 2007, Briesch et al. 2009). Overall, although contexts vary and the effects are not uniform, extant literature points out that variety decisions are economically consequential for consumers' behaviors.

We visualize the literature on assortment reduction using experiments in Online Appendix A. We observe a predominant focus on variety in online or offline supermarkets, whereby behavioral frictions may be less pronounced due to frequent knowledge of the category and not overwhelming choice sets. Therefore, exploring how assortment changes unfold in high-stakes real-world settings of online platforms remains underdeveloped.

Consumers' responses to choice sets are not homogeneous. Contextual effects of relative popularity, familiarity with the choice domain, or structured preferences have been shown to moderate such responses (Park and Lessig 1981, Prelec et al. 1997, Chernev 2003b, Kamenica 2008, Mogilner et al. 2008). For example, Prelec et al. (1997) shows that customers might be unsure of which product attributes they value the most but can guide their own purchase decision by drawing inferences about popularity and others' preferences. Relatedly, Mogilner et al. (2008) shows that consumers in unfamiliar choice domains are more sensitive to categorization in finding their own preferences and subsequent satisfaction. In our work, by exploiting variation in customers' proximity to the destination, we show a novel effect of familiarity with the assortment: it moderates search costs and explains heterogeneous behaviors in terms of consideration set formation, preferences for niche versus popular choices, as well as conversion rates when the choice set changes.

2.2. Formation of Consideration Sets

Our work also contributes to the literature on the formation of consideration sets and choice processes. Consideration sets are typically modeled through two main approaches: (1) screening based on a subset of product attributes and (2) including products whose expected incremental benefit outweighs the cognitive cost incurred to evaluate them. We provide a summary in Online Appendix B.

In the first approach, products are included in consideration sets if a subset of product attributes meets certain screening criteria. Shugan (1980) argues that adopting a screening rule based on a subset of attributes is a rational outcome when the consumer is subject to cognitive costs. In this vein, Gilbride and Allenby (2004) propose various screening rules where one or multiple criteria must be satisfied for the product to be included in the consideration set. Rather than using a predetermined rule, Moe (2006) infers criterion attributes during the consideration set formation stage based on observed choice decisions and allows consumers to evaluate different sets of product attributes. Aouad et al. (2021) adopt a similar screening rule as proposed by Gilbride and Allenby (2004) to form consideration sets and study the computational complexity of assortment optimization under the consider-then-choose framework.

In the second approach, the cognitive cost of evaluating each alternative during the purchase decision-making process is explicitly modeled. Specifically, the consumer first determines which items to include in the consideration set based on prior knowledge of item attributes, without incurring any cost. Subsequently, the customer undergoes a thorough evaluation of the items

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in such consideration set, learning the true values of the attributes while incurring a per-unit evaluation cost. Importantly, the consumer incorporates the evaluation cost upfront in the first stage when deciding whether to include an additional product into the consideration set. Thus, the formation of the consideration set ultimately hinges on striking a balance between the expected incremental benefit gained from including additional promising products and the associated evaluation cost. Related studies that utilize this method include Hauser and Wernerfelt (1990), De los Santos et al. (2012), Wang and Sahin (2018), and Donnelly et al. (2023). Meanwhile, Derakhshan et al. (2022) examine the best product rank, although customers also incur a position-dependent screening cost in the first stage to observe the preference weight of the product in addition to the evaluation cost.

Our consider-then-choose setup is similar to Wang and Sahin (2018) and Donnelly et al. (2023) but diverges from them as follows. First, the process of forming expected utility and sorting all products within an assortment results in cumulative tiredness and fatigue, which carries over to the evaluation stage. To better model this behavioral add-on, search costs are not constant but an increasing (general) function of the assortment size. Second, we introduce customer heterogeneous preferences for product attributes. As we develop later, these features are fuzzy and uncertain in the early stages, but its value is revealed when the products are examined. These two novel aspects enable us to investigate how the consideration set formation and purchase decision processes are influenced by customer heterogeneity and the assortment size. Consequently, we provide a psychologically rich guiding framework that articulates timely and managerially relevant problems for online platforms, such as the value of niche options and choice overload concerns.

3. Empirical Setting: Online Travel Platform

We collaborate with Despegar, one of the leading online travel platforms worldwide offering flights, hotels, car rentals, cruises, and tourist packages. Similar to Expedia or Booking, the platform acts both as a price aggregator (allowing comparisons between most viable alternatives), as well as a merchant (facilitating bookings for the trip through its website, rather than redirecting to the hotel website). This feature allows to track the customer path, from the landing page, search behavior, clicks to hotels, until an eventual purchase. We describe the data sets in Sections 3.1 and 3.2 and the design of the field experiment in Section 3.3.

3.1. Data Description

We use two clickstream data sets: a field experiment data set covering three destination cities and an observational data set. The observational data (described in Online Appendix D) includes 10 million online user logs and more than 2,000 destination cities, from which we recover clickstream data from a different period for the three cities that participated in the experiment. Although we rely on the field experiment to establish causality for the effects of the assortment size reduction, when possible, we repeat our analyses on the observational data set.

Each time a new user browses the website, the user receives a cookie which allows the company to tag and track individually. An HTTP cookie is a piece of data that is stored on a user's browser, which is used by the website to recognize each time the user returns and starts a new session. This process is repeated until cookies are erased or cleared (cookie churn).

The user-level browsing activity belongs to one of the five consecutive stages in the funnel: (1) the landing page which is the first interaction of the user with the website; (2) the search page after entering a specific criteria (e.g., destination, dates) and clicking the search button; (3) the detail page which shows up after clicking on a specific hotel; (4) the checkout stage after adding an option to the cart, and (5) the booking page after a purchase is completed. These five visits are concatenated with the user identifier.

In addition, the data include descriptive features of the hotels and the search query. For example, a booking confirmation has its corresponding number of nights, price, hotel stars, number of rooms, and number of guests. We also infer the location of the user based on the IP address of the originating query.

Table 1 shows summary statistics. During the experiment period, there are 1.86 million observations, more than 322,000 distinct users (to be defined below), 601,700 searches, 184,100 checkouts, and 18,000 bookings. Purchases are economically meaningful: the median and average transaction is \$177–\$268 dollars, respectively.

Table 1. Descriptive Statistics

	Cities of Buenos Aires, Rio de Janeiro, and Sao Paulo
Observations	1,858,900
Users	322,800
Days[a]	47
Searches	601,765
Checkouts	184,169
Bookings	18,011
Average price[b]	268.0
Median price[b]	177.0
Average nights[c]	2.6

Note. Includes multiple visits per user if users browse in different sessions.
[a]Days included in the experiment clickstream data.
[b]Average price and median price in U.S. dollars conditional on a purchase.
[c]Average length of stay conditional on a purchase.

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3.2. Web-Scraping Hotel Covariates

To enhance the richness of hotel covariates, we web-scraped Despegar's site for the hotel identifiers in our experimental and observational data sets. In particular, we collected (a) a night's stay price (averaged over multiple future dates), (b) location coordinates, (c) review score, (d) number of reviews, (e) distance from downtown, and (f) share of customers' reviews based in the hotel's country.

Figure 1 visualizes the customer journey (Online Appendix C shows more examples). Upon clicking search, the website returns a list of hotel results—and each hotel snippet is referred to as the thumbnail. As per Figure 1(a), the thumbnail depicts useful but limited information. For example, it displays the distance from downtown (but not the location) or the overall score (but not the reviews). Presumably, the information in the thumbnail is not sufficient to make a decision. However, clicking on one option leads to the hotel page, which displays abundant details. As per Figure 1(b), it shows the address, a map, the distance to some key touristic spots in the city, hotel amenities, and more. Additionally, as per Figure 1(c), customers can click on the review score and observe the reviews posted by past travelers (and their country).

Finally, the location coordinates allowed us to take a step further in collecting hotel-level covariates. We obtain the top 20 touristic attractions in each city from TripAdvisor. We focus on the median distance and number of attractions within 2 km of the hotel, capturing its appeal to touristic attractions.

3.3. Field Experiment in Online Assortments

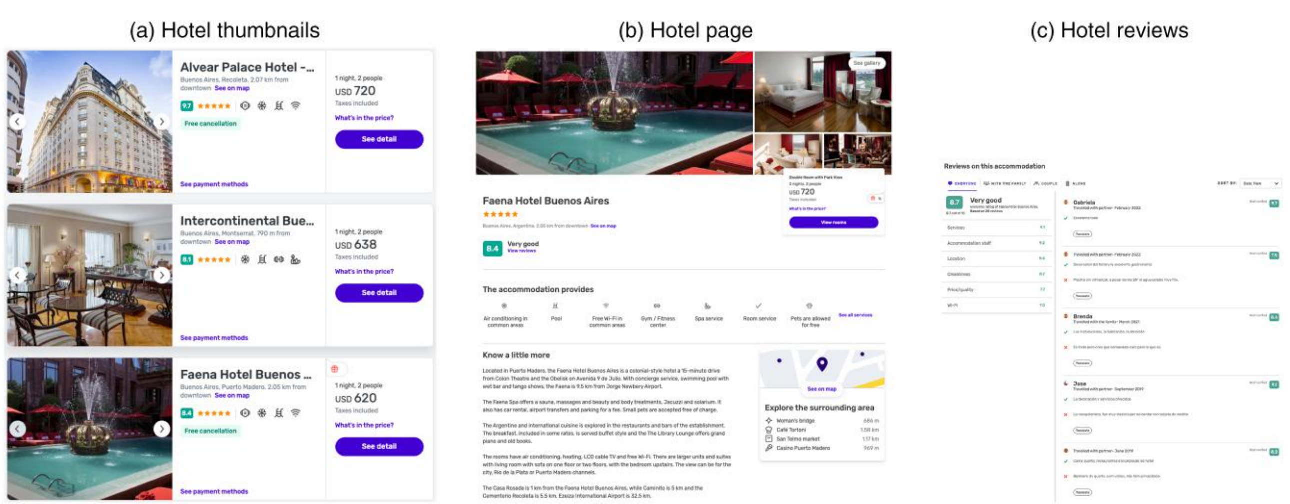
In collaboration with the online platform, we design a field experiment to study the effects of reducing the assortment size on the search and shopping behaviors. The design can be summarized into four steps.

First, the experiment is implemented on users that search for accommodation in three cities: Buenos Aires (Argentina), Rio de Janeiro (Brazil), and Sao Paulo (Brazil). All users searching hotels in those three cities are exposed to this experiment regardless of their location, that is, where the query originates from.

Second, each user is randomly assigned to a treatment or control condition according to a traffic splitting algorithm meeting a target ratio. For example, a target ratio of 50% means that half of the users are assigned to treatment and half to control. The functionality of the platform remains exactly the same across conditions, except for the assortment size. Reassuringly, the same user is assigned to the same condition each time a search is done for those cities. This is achieved as the web page places a cookie that lasts for seven days, and each time the user returns to the website, the cookie identifies the original treatment assignment. Therefore, a distinct user can be defined as the browsing activity covering all sessions that have a single cookie in common. We only use the clickstream data of the first seven days for each user. The treatment assignment probability was 25% in Buenos Aires, 30% in Rio de Janeiro, and 50% in Sao Paulo. The design carefully follows the usual random treatment assignment and allows for causal inference.

Third, in deciding the assortment reduction, no exact threshold exists in the literature. Because online platforms have a remarkably large inventory (Kim et al. 2010, Brynjolfsson et al. 2011), we implemented a reduction that would be relatively meaningful to the assortment offered without jeopardizing the external validity. For example, although a reduction of 90% is conceptually intriguing, consumers could perceive an artificial setting. In our case, the assortment was reduced between 40% and 60%. The choice set offered (and the set not offered) to a given user is not available because it is updated in real-time based on inventory changes

Figure 1. (Color online) Customer Journey: Despegar Example



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(options become available or unavailable) and query conditions (requirements in the search query). Importantly, the experiment of choice set reduction can be interpreted as being "reasonably large, but not ecologically unusual" for hotel bookings, consistent with the early guidelines of Iyengar and Lepper (2000).

Fourth, the assortment was reduced by randomly excluding options from a pool of low-selling hotels. This resembles the existing literature (Broniarczyk et al. 1998, Boatwright and Nunes 2001, Borle et al. 2005). If options were removed completely at random, the smaller choice set would exclude options which are strongly preferred (Iyengar and Lepper 2000, Chernev 2003b), making the larger choice set mechanically superior. Indeed, Broniarczyk et al. (1998) tested 25%, 50%, and 75% reductions in a supermarket category whereby "only low-preference SKUs were deleted" allowing to examine "situations in which favorite alternatives are available, because retailers altering categories will clearly try to maintain those items their shoppers want." This logic is also observed in Kamenica (2008, p. 2129), noting that "the average popularity of the available varieties is decreasing in the breadth of the product line." In simpler terms, in testing the breadth of the soda category, it would be managerially unwise to (randomly) remove Coca-Cola Zero.

4. Consideration Set Formation

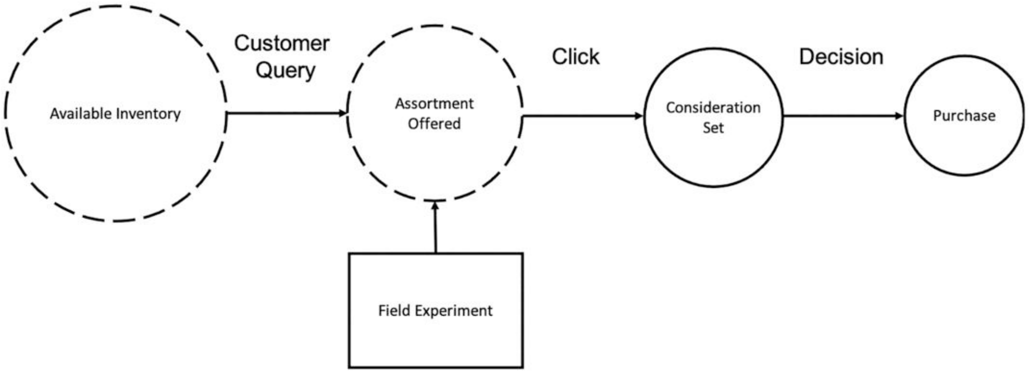
The customer journey in online platforms can be generally characterized by four stages. We visualize this journey in Figure 2.

- *Inventory*. The platform (Despegar) has an inventory of hotels in each destination city.
- *Choice Set*. The customer visits the website and enters a search query. In our case, the customer searches for hotels in a target city and dates. Upon clicking "search," the platform returns the choice set eligible for purchase. A smaller bubble for the choice set reflects the fact that some options from the inventory may not be available (e.g., sold out). However, the choice set is typically quite large.
- *Consideration Set*. The customer observes key but summarized hotel attributes (e.g., score) and forms a smaller consideration set from the assortment offered. The consideration set is comprised by the options selected by the customer for closer inspection. In our case, we assume a customer adds an option to the consideration set when clicking on it (more details follow).
- *Purchase*. Upon examining the consideration set, the customer learns the accurate hotel attributes (e.g., reviews and amenities). Then the customer decides whether and which option to book.

Our study begins when the choice set is displayed. As opposed to the grocery environment, online platforms tend to display a large menu of options—for example, travel platforms may display hundreds of hotels to choose from. Although some options may be irrelevant straightaway, it is unfeasible to examine so many options. Abundant research emphasizes the role of "search costs" while browsing, evaluating options, and making a decision (De los Santos et al. 2012).

However, not all customers may exhibit the same shopping frictions. We examine a dimension of customer heterogeneity: familiarity with the assortment. Familiarity can be defined as subjective knowledge, which captures the construct of familiarity (Rooderkerk and Lehmann 2021). Although familiarity effects in high-stakes online shopping received little attention, its conceptual role in the choice process is not new. Several studies in behavioral sciences describe how context effects and familiarity moderate the selection of choices (Park and Lessig 1981, Park et al. 1989, Prelec et al. 1997, Chernev 2003b, Mogilner et al. 2008). For instance, Chernev (2003a) posits that consumers with articulated ideal points exhibit a less cognitively burdensome search process. Importantly, the early work of Alba and

Figure 2. Shopping Funnel in Online Platforms: From Inventory to Assortment Offered to Formation of Consideration Sets, and to Purchase Decision



Notes. The (shrinking) size of the bubbles reflects that the menu of options sequentially declines throughout the funnel. Our analysis ignores filtering tools.

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Hutchinson (1987, p. 411) defines familiarity as "experiences that have been accumulated by the consumer" and states that "increased product familiarity results in increased consumer expertise." Similarly, Park and Lessig (1981, p. 225) explain that high-familiarity decision makers "can achieve information search and processing efficiency due to her high level of familiarity."

With these ideas in mind, we bring the notion of familiarity to our setting of online travel and develop our first empirical hypothesis about its role in the search process. In particular, we hypothesize that consumers who have high familiarity with the assortment bear lower search costs and, as a result, are able to add more options to the consideration set compared with low-familiarity customers.

Hypothesis 1. *High-familiarity (low-familiarity) consumers form a larger (smaller) consideration set size.*

We operationalize familiarity by exploiting the user's geographic location. Consumers in closer proximity to the destination have subjectively accumulated bits of experiences and information pieces which inform about the attributes of the assortment and the city, leading to heterogeneous shopping patterns, compared with consumers farther away from the destination. In the words of words of Coupey et al. (1998), high-familiarity customers are expected to exhibit relatively higher "prior knowledge and experience" with the choice domain. Therefore, customers whose IP address of the query is in the same country as the destination city are classified as high-familiarity consumers and otherwise as low-familiarity consumers. Although purchase frequency is also used to measure familiarity (Alba and Hutchinson 1987, Rooderkerk and Lehmann 2021), hotel bookings are not characterized by recurring purchases in a short period.

We see motivating evidence for this operationalization in Figure 1(c), showing its interplay in the reviews: All customers of the Faena Hotel are low-familiarity customers. Another piece of empirical support comes from high-familiarity users having more informed search patterns, as captured by their greater likelihood to apply filters when browsing options (see Online Appendix E). Still, we provide a caveat that city proximity within the country may further moderate search efforts, which we lack in our data.

As to measuring the size of the consideration set, we use two measures: distinct hotels clicked and clicks to hotel pages (henceforth, click-through rate (CTR)). A click-based measure of the consideration set resembles Moe (2006), Ursu et al. (2020), and Aouad et al. (2024). For example, Aouad et al. (2024, p. 2) write: "we define each customer's consideration set precisely as the set of products they have clicked on." Intuitively, customers are initially confronted with a relatively extensive menu and the information available for each option is limited to make a decision (Figure 1). However, once a product is clicked, the customer learns key product attributes to make a final decision. In other words, clicking a product is live proof that the customer is *considering* that option; that is, the customer is willing to spend time and effort to review the hotel more carefully. We acknowledge that this operationalization is not perfect, and we may neglect options that customers evaluate through other means. For convenience, all empirical variables are also defined in Online Appendix F.

Table 2 report the results. We consistently find that high-familiarity customers form larger consideration sets. Consider Panel B: High-familiarity customers click on average 3.97 distinct hotels compared with 3.59 clicks for low-familiarity customers, representing a 10.5% relative difference. (The data set includes both the treatment and control conditions as we are not interested in the treatment effect, but in the overall patterns across familiarity segments.) As some destination cities have more hotel choices than others, we normalize the number of distinct clicks over the total number options clicked and use the percentage of hotels clicked as an alternative

Table 2. Formation of Consideration Sets Using Clickstream Data

	High familiarity	Low familiarity	Difference
Panel A: Observational data			
(1) Consideration set size[a]	1.75 (0.01)	1.64 (0.01)	0.11*** (0.01)
(2) Normalized consideration set size[b] (×100)	15.44 (0.08)	14.36 (0.07)	1.08*** (0.11)
(3) CTR[c]	2.20 (0.01)	2.12 (0.01)	0.08*** (0.02)
Panel B: Experiment data			
(1) Consideration set size[a]	3.97 (0.01)	3.59 (0.02)	0.38*** (0.02)
(2) Normalized consideration set size[b] (×100)	68.83 (0.28)	55.58 (0.36)	13.25*** (0.48)
(3) CTR[c]	4.42 (0.02)	3.96 (0.02)	0.47*** (0.03)

[a]Consideration set size denotes the average number of distinct hotels browsed at the user level, unconditional on a purchase.
[b]Consideration set size, as a percentage of the distinct options in each city.
[c]CTR denotes the average click-through rate to hotel pages at the user level, unconditional on a purchase. Standard errors reported in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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measure of the consideration set. High-familiarity customers click on 0.69% of the total listings compared with 0.56% low-familiarity customers. Furthermore, we investigate the difference in the CTR and, once again, observe a similar effect. We find a similar pattern of results using the observational data (Panel A). Thus, these estimates support Hypothesis 1.

We report several robustness specifications. One may point out that the consideration set effect is confounded by user characteristics generated by the sampling bias between high- and low-familiarity customers. To address this, we estimate the following fixed effects model:

$$|N|_{ij} = \alpha + \beta \mathbb{I}_{\{type_i = HF\}} + Z_i + W_j + \epsilon_{ij}, \qquad (1)$$

where $|N|_{ij}$ is the log-transformed consideration set size of customer i in city j, $\mathbb{I}_{\{type_i=HF\}}$ denotes the indicator variable that takes a value of one when customer i is defined as high-familiarity (or zero otherwise), and Z_i and W_j control for user search query i (number of guests) and city j fixed effects, respectively.

Once again, high-familiarity consumers form larger consideration sets (see Online Appendix G). One may argue that differences in the consideration set are driven by differences in peculiar search query patterns. However, we observe that customers are not searching for hotels in systematically peculiar locations (Online Appendix H). Additional model estimates, including effect sizes, are reported in Online Appendix M.

In sum, we established that high-familiarity customers form larger consideration sets compared with low-familiarity customers (Hypothesis 1). Does familiarity also drive heterogeneous tastes for which hotels customers end up purchasing? We explore this next.

5. Heterogeneous Tastes for Niche vs. Popular Hotels

We showed that familiarity with the choice domain amplifies the consideration set size (Hypothesis 1). Presumably, familiarity can also shift relative weights ("attention") of attributes in the decision (Johnson and Russo 1984, Alba and Hutchinson 1987, Coupey et al. 1998). For example, high-familiarity customers may have accumulated subjective knowledge about convenience nearby and public transportation access—reducing their sensitivity to distance or to travelers' comments about traffic.

We hypothesize that customers have heterogeneous tastes for hotels, namely high-familiarity customers exhibit a relatively greater appeal for niche hotels compared with low-familiarity customers. To examine the role of niche hotels, we use the operationalization of Brynjolfsson et al. (2011)—defined as those products in the bottom 50% of the transactions' distribution. When translated to the context of hotel bookings: a niche hotel belongs to the subset of hotels in a city that during the relevant time period accounts for the bottom 50% of transactions. The hypothesis can be stated formally as follows.

Hypothesis 2. *High-familiarity (low-familiarity) consumers are more (less) likely to purchase niche options.*

What makes a hotel niche? Before testing Hypothesis 2, it is helpful to get confidence that niche hotel features cater narrow-appeal choices. To address this, we utilize hotel covariates web-scraped off Despegar (Section 3.2). We then estimate the following model:

$$Attractions_{kj} = \alpha + \beta_1 \mathbb{I}_{\{Niche_k = 1\}} + W_j + \epsilon_{kj}, \qquad (2)$$

where $Attractions_{kj}$ denotes the number of touristic attractions within 2 km of hotel k in city j (as per TripAdvisor); $\mathbb{I}_{\{Niche_k=1\}}$ denotes the indicator variable that takes a value of one if hotel k in city j is defined as niche (or zero otherwise); and W_j denotes city fixed effects. We estimate Equation (2) for all customer bookings in the observational and experiment data sets. In two other specifications, we re-estimate Equation (2) for $Distance_{kj}$, defined as the (log) median distance of the pairwise distance between hotel k in city j to all top 20 touristic attractions, as well as for $Reviews_{kj}$, defined as the (log) number of reviews for hotel k.

The model estimates are reported in Online Appendix I. As per columns (1) and (2), niche hotels have roughly 0.7 fewer attractions nearby and are 6.8% (exp(0.066) − 1) more distant from touristic spots. We are mindful that some options may be generally unattractive and therefore low sales may not capture a niche attribute—that is, a "narrow appeal" feature serving a small market (Tucker and Zhang 2011). To address this, column (3) shows that niche hotels have 78% (exp(−1.508) − 1) fewer number of reviews. Importantly, the effect is robust to controlling for overall hotel score and distance to downtown (Online Appendix I). That is, among equally good hotels, niche hotels have fewer customers' reviews. Collectively, these estimates provide compelling evidence that niche hotels exhibit "off the beaten track" features. Still, we acknowledge that our empirical strategy ignores some characteristics, for example, aesthetics or polarization and valence in the text reviews.

We begin our tests for Hypothesis 2 by visualizing the options purchased by high- versus low-familiarity customers (see Online Appendix I). We observe that close to 70% of the hotels purchased by high-familiarity consumers have a market share lower than 1%, whereas the analogous estimate is 55% for low-familiarity consumers. The right tails are also informative of the purchase behavior: Close to 5% of the hotels of low-familiarity consumers have a market share higher than 4%, whereas those market shares are only observed in close to 1% of the hotels of high-familiarity consumers. Furthermore, we compute the Herfindahl–Hirschman

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Index (HHI), a commonly used measure of market concentration. The HHI is defined as $\sum_{k\in j(f)} s_k^2$, namely the sum of squared market shares for all hotels k in the relevant city j computed across bookings by customer segment. The hotel market HHI is 0.81 and 0.53 for low-familiarity customers and high-familiarity customers, respectively. Thus, this evidence strongly indicates that high-familiarity consumers tend to purchase narrow appeal choices, as shown by the low market shares of their hotels.

Various empirical strategies to test Hypothesis 2 yield similar conclusions. We focus on the hotels that intersect the consideration sets of high- and low-familiarity consumers, and then we compute the relative popularity ratio for all possible combinations of the hotels. Row (1) of Table 3 reports significant differences in the popularity. Next, we test the definition of niche options following Brynjolfsson et al. (2011). Row (2) reports that high-familiarity customers exhibit a (relative) 31% higher probability to book a niche hotel compared with low-familiarity customers. Overall, our findings provide novel and strong support to the value of narrow-appeal choices (Brynjolfsson et al. 2011, Tucker and Zhang 2011).

Furthermore, we examine the distribution of city-level hotel market shares. We restrict the sample to the same number of transactions and test whether high-familiarity users purchase niche hotels, whereas low-familiarity users tend to cluster at popular hotels. The hotel market share is defined as the ratio of transactions in a given hotel to the number of transactions in that destination city. Row (3) shows that high-familiarity customers tend to book hotels with lower market shares and are less likely to coincide on the same hotel, compared with low-familiarity customers. The pattern is similar using the 25th and 75th percentiles (Online Appendix J). Moreover, the findings are consistent in both the observational and experiment clickstream data sets. Additional robustness tests are reported in Online Appendix J.

We conclude this analysis by documenting the extent to which high-familiarity customers purchase hotels which exhibit niche features. More precisely, we estimate the following model:

$$Attractions_{ikj} = \alpha + \beta_1 \mathbb{I}_{\{type_i=HF\}} + \beta_2 Score_{ik} + \beta_3 Price_{ik} + W_j + \epsilon_{ikj}, \tag{3}$$

where $Attractions_{ikj}$ denotes the number of touristic attractions within 2 km of hotel k in city j purchased by customer i; $\mathbb{I}_{\{type_i=HF\}}$ denotes the indicator that takes value 1 if customer i is high-familiarity; $Score_{ik}$ denotes the score of hotel k; $Price_{ik}$ denotes the average price per night of hotel k; and W_j denotes city fixed effects. In three other specifications, we re-estimate Equation (3) for (a) $Distance_{ikj}$, defined as the (log) median distance of the pairwise distance between hotel k in city j to all top 20 touristic attractions; (b) $Reviews_{ikj}$, defined as the (log) number of reviews of hotel k; and (c) $RatioHF_{ikj}$, defined as the ratio (0%–100%) of high-familiarity customers' reviews to the total number of reviews for hotel k.

The results are shown in Table 4. Overall, high-familiarity customers book hotels characterized by narrow appeal features compared with low-familiarity customers. In particular, niche hotels tend to be more distant from the key touristic spots, have lower reviews for an equal quality, and are more frequently booked among other high-familiarity customers. Therefore, the evidence supports Hypothesis 2.

These findings unveil heterogeneous preferences between low- and high-familiarity customers. As we theoretically develop later, customers may have heterogeneous sensitivity toward attributes that are somewhat fuzzy in the early stages of the funnel. For example, the distance between the hotel to a point of interest is unclear from the search results (Figure 1(a)). In the thumbnail page, we only observe the "distance to downtown"—which only informs a distribution of distances in a circle. The address, amenities, or guests'

Table 3. Heterogeneous Preferences for Niche Hotels

	High familiarity	Low familiarity	Difference
Panel A: Observational data			
(1) Relative popularity[a]	1.17	1.18	−0.01 (t = 3.91***)
(2) Prob. buying niche (bottom 50%)[b]	0.17 (0.01)	0.13 (0.01)	0.04*** (0.01)
(3) Hotel market share (%)[c]	1.37 (0.03)	1.44 (0.03)	−0.07* (0.04)
Panel B: Experiment data			
(1) Relative popularity[a] (t-test)	1.88	1.86	0.02 (t = 2.91***)
(2) Prob. buying niche (bottom 50%)[b]	0.13 (0.01)	0.11 (0.01)	0.02*** (0.01)
(3) Hotel market share (%)[c]	0.96 (0.02)	1.16 (0.02)	−0.19*** (0.03)

[a]Reports the t-test of the relative popularity ratio.
[b]Denotes the probability that a user buys a niche option.
[c]Denotes the average market share of a single hotel in a given city using the same number of transactions across segments. Standard errors reported in parentheses, unless otherwise specified.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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Table 4. Heterogeneous Preferences for Niche Hotels

	Observational data				Experiment data			
	Attractions (1)	Distance (2)	Reviews (3)	Ratio H-F (4)	Attractions (5)	Distance (6)	Reviews (7)	Ratio H-F (8)
High familiarity	−0.237***	0.093***	−0.172***	3.089***	−0.278**	0.020***	−0.022***	3.075***
	(0.062)	(0.009)	(0.030)	(0.494)	(0.019)	(0.002)	(0.009)	(0.192)
Constant	8.546***	0.875***	8.550***	113.227***	5.693**	1.342***	7.993***	70.747***
	(0.338)	(0.050)	(0.163)	(2.678)	(0.098)	(0.010)	(0.046)	(0.992)

Notes. Columns (1), (2), (3), and (4) estimate the number of touristic attractions within 2 km, the (log) median pairwise distance to the touristic attractions, the (log) number of reviews, and the share of high-familiarity reviews, respectively, using the observational data. Columns (5)–(8) estimate the analogous specifications using the experiment data. All specifications include controls for city, hotel score, and hotel price. Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

comments are crystallized when clicking on it (Figure 1(b)). It is plausible that high-familiarity customers gain less value from being close to the opera. Said differently, proximity to Teatro Colon (among the best opera houses in the world) may be a powerful "stamp" for a low-familiarity customer, overweighing the decision. A high-familiarity customer is not against the opera, but does not mind being a little further away and hence stands to benefit from other narrow-appeal features the hotel has to offer.

To summarize, we showed that high-familiarity versus low-familiarity customers have heterogeneous behaviors when forming the consideration set, as well as when making a purchase. More specifically, high-familiarity customers tend to form larger consideration sets (Hypothesis 1) and high-familiarity (low-familiarity) customers are more likely to purchase niche (popular) options (Hypothesis 2). Having established these two critical facts about the *consideration stage* and the *purchase stage*, we explore the following question: How do customers respond to a reduction in the assortment size?

6. Shrinking the Assortment in a Field Experiment

Online assortments can get overwhelming. For instance, a brick-and-mortar Suning store (China's electronics retailer) carries 25,000 SKUs, whereas its online store offers 15 million SKUs (NFR 2017). Thus, firms often wonder whether "less is more": Could the business be better off with fewer options?

We run a field experiment to test the effect of reducing the assortment size (Section 3.3). The platform randomly assigned users to either (a) a control condition in which users are presented with the choice set as usual or (b) a treatment condition in which users are presented with about a 50% smaller choice set.

We hypothesize that reducing the choice menu leads users to form smaller consideration sets, regardless of their familiarity. If the costs of search are not too large, reducing the assortment prevents them from adding more options—that is, options that would have been added had they been offered. Intuitively, the overall pie is smaller and therefore the customer will click on fewer alternatives.

However, for its effect on the purchase decision, we should be mindful of customer heterogeneity (Sections 4 and 5). On one hand, high-familiarity customers should be less likely to purchase when the assortment is reduced. This occurs due to two mutually reinforcing factors: high-familiarity customers consider a larger choice menu, as well as tend to purchase niche options. Therefore, shrinking the assortment (by cutting low sellers) leads to a lower probability of conversion because (a) there is a sharper decrease in the consideration set and (b) many of their appealing niche options are not there. On the other hand, the conversion rate reverses for low-familiarity customers. As they find it more costly to search and navigate through options, removing "noisy" hotels (e.g., narrow-appeal options that would have never been relevant because they are far from the opera) allows them to consider (fewer) options that are a better match. As a result, their likelihood of buying increases. We formalize these implications as Hypotheses 3a and 3b, as follows:

Hypothesis 3a. *When the assortment size is reduced, consumers (regardless of their familiarity) form a smaller consideration set.*

Hypothesis 3b. *Overload effect: When the assortment size is reduced, high-familiarity (low-familiarity) consumers are less (more) likely to make a purchase.*

We test Hypotheses 3a and 3b through the following model:

$$Y_{ij} = \alpha + \beta_1 \mathbb{I}_{\{Treated_i=1\}} + \beta_2 Score_{ik} + \beta_3 Price_{ik} + Z_i + W_j + \epsilon_{ij}. \tag{4}$$

We examine three specifications where Y_i in Equation (4), the outcome variable, is the log-transformed size of the consideration set of user i in city j (or log-

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transformed hotel CTR) or a purchase indicator of user i in city j. The latter is defined as a binary variable that takes a value of one if user i completed a purchase (or zero otherwise). Additionally, $\mathbb{I}_{\{Treated_i=1\}}$ denotes the indicator function that takes a value of one if user i was in the treatment condition displaying a smaller choice set (or zero otherwise); $Score_{ik}$ and $Price_{ij}$ control for the average hotel score and price considered by user i in city j; and Z_i and W_j control for search query and city fixed effects, respectively. The model is estimated separately by customer segment.

The results are shown in Table 5. Consider columns (1) and (3): When consumers are offered a smaller choice set, the negative coefficient indicates that both high- and low-familiarity customers form a smaller consideration set size. Moreover, the effect is more pronounced for high-familiarity customers. For example, when the assortment is reduced, the consideration set declines by 5.0% for high-familiarity users and by 3.1% for low-familiarity users. As per columns (2) and (4), we observe the same pattern of results when we re-estimate Equation (4) for the CTR to hotel pages. Thus, the evidence supports Hypothesis 3a.

Online Appendix K reports similar findings when we re-estimate Equation (4) using linear measures. Online Appendix L reports robustness results using the seemingly unrelated regressions (SUR) method.

Next, we examine the effect on the conversion rate. Columns (5) and (6) in Table 5 show that shrinking the choice set reduces the purchase probability by 0.6 percentage points for high-familiarity customers, whereas it lifts the purchase probability by 0.4 percentage points for low-familiarity customers. These effects represent a 11% drop and a 14% increase in the conversion rate—that is, the choice set size has economically meaningful effects. Overall, these findings support Hypothesis 3b. These magnitudes are qualitatively in line with previous studies, finding effects between 4% and 12% (in absolute value) when removing low-selling SKUs from supermarket shelves (Dreze et al. 1994, Broniarczyk et al. 1998, Boatwright and Nunes 2001).

We implement various robustness checks. We find similar results using a nonlinear Logit model (Online Appendix K). A complementary test is the add-to-cart conversion rate (Online Appendix K), where we find a significant decline in the conversion rate for high-familiarity consumers but an increase for low-familiarity consumers. Finally, consistent with these findings, we infer the set of hotels removed in the treatment condition and find that they tend to exhibit narrow-appeal features (Online Appendix N). However, these features do not necessarily make the hotel appealing to high-familiarity customers—the platform could be removing a large fraction of hotels with generally (unobservable) unattractive features, regardless of the customer segment.

6.1. Choice Overload

It seems paradoxical that variety can be detrimental to choice—Conventional wisdom suggests that consumers are always better off with more options. Yet, our findings reveal that the effects of too many options interplay with customer heterogeneity: Low-familiarity (high-familiarity) consumers are more likely (less likely) to purchase when they are offered fewer choices. This phenomenon, where consumers are deterred from purchasing due to the sheer number of options, is referred to as *choice overload*. As Chernev et al. (2015, p. 335) explains, "compared to individuals not experiencing choice overload, those experiencing overload are less likely to make a choice from a particular assortment." To the best of the authors' knowledge, this is a novel finding in the context of online platforms.

Choice overload (or over-choice) is typically attributed to increased task difficulty, decision delay, and cognitive burden associated with a large menu of options (Shugan 1980, Shafir et al. 1993). The seminal work of Jacoby (1977, p. 569) notes, "information

Table 5. Consideration Set, Click-Through Rate, and Purchase

	Field experiment					
	Consideration stage				Purchase stage	
	High-F		Low-F		High-F	Low-F
	CS (1)	CTR (2)	CS (3)	CTR (4)	Purchase (5)	Purchase (6)
Treatment	−0.051***	−0.046***	−0.030***	−0.021***	−0.006**	0.004**
	(0.004)	(0.005)	(0.007)	(0.007)	(0.003)	(0.002)
Constant	2.094***	2.127***	2.230***	2.243***	0.189***	0.034***
	(0.027)	(0.028)	(0.040)	(0.042)	(0.017)	(0.014)

Notes. Columns (1), (2), and (5) estimate the effects of reducing the assortment on consideration set size, click-through rate (CTR), and purchase probability, respectively, for high-familiarity customers; and columns (3), (4), and (6) estimate the analogous specifications for low-familiarity customers. All specifications include controls for city, hotel score, hotel price, and search query. Standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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overload refers to the fact that there are finite limits to the ability of human beings to assimilate and process information during any given unit of time." Furthermore, Chernev et al. (2015, p. 335) describes it as "a scenario in which the complexity of the decision problem faced by an individual exceeds the individual's cognitive resources" and in particular "one in which the decision complexity is caused, at least partially, by the (large) number of available decision alternatives."

Over-choice can reasonably manifest in online platforms: (a) consumers confront an overwhelming choice set; (b) platforms display fuzzy information about each product in the early stages of the funnel (Figure 1); and (c) there are nonnegligible search costs to evaluate each product before making a decision. Despegar's experiment is reminiscent of the "Editor's Pick" feature often observed in the marketplace—such as in Spotify's or Goodreads'—which provides a curated assortment to reduce decision fatigue and increase the likelihood of conversion, particularly for consumers who might feel overwhelmed by too many choices.

Next, we develop Hypotheses 1, 2, 3a, and 3b in a theoretical model. The intent of the model is to generalize our learnings from the field to various platform settings.

7. Behavioral Model of Customer Journey in Online Platforms

We would like to take a step back from Despegar and offer a general theoretical framework. This model helps us organize our thoughts about the role of customer heterogeneity and behavioral frictions in the shopping funnel, speaking to various online platforms. Our model follows the consider-then-choose setup (Hauser and Wernerfelt 1990, Wang and Sahin 2018) and incorporates heterogeneous consumers. To make our analyses more generalizable, we abstract from the concept of familiarity in our empirical analyses and instead assume that there are multiple customer segments who exhibit (a) different search costs and (b) heterogeneous preferences for specific product features.

The customer's decision process is sequenced into a *consider stage* and a *choose stage*. A two-stage process is reasonable when consumers cope with wide online assortments (Hauser et al. 2010, Van Nierop et al. 2010). In the *consider stage*, the customer forms the consideration set from the assortment offered by undergoing a costless search. We define N as an assortment with size $|N|$, where $|\cdot|$ refers to the cardinality of a set, and define Φ as the consideration set (Φ is a subset of N). Next, in the *choose stage*, the customer closely examines each option in the consideration set at a per-unit search cost, shaped by the customer type and the assortment size. As in Aouad et al. (2024), the customer lacks full information about the options offered by the platform; however, this uncertainty is cleared once a given option is examined. The customer then chooses the product with the highest utility. The funnel is summarized in Figure 3.

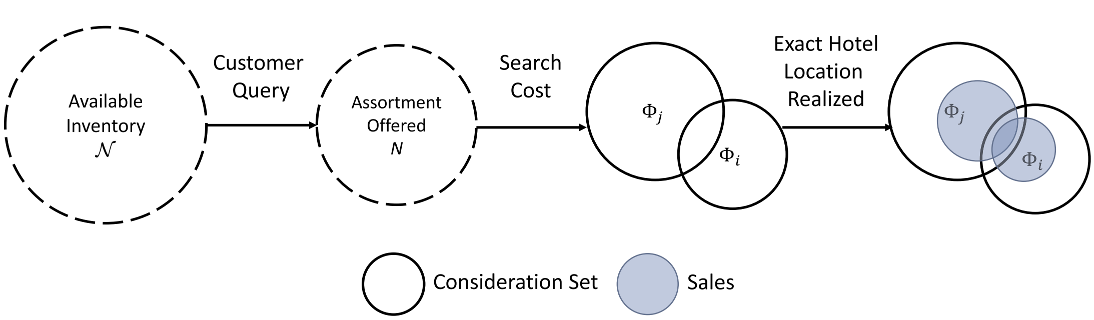
7.1. Customer Utility

We define $\mathcal{N}$ as the entire set of available products. It can be interpreted as the SKUs in the warehouse of an online retailer or, as in the empirical setting, all potential hotels for a given destination. The subset of options *offered* by the platform is defined as N, which is the assortment that customers actually observe on the screen. It is a subset, that is, $N \subseteq \mathcal{N}$, because some options may be sold out or not compatible with the customer query. In addition, we assume that there are I segments of consumers, each characterized by different search costs and tastes for product features. We use a random utility model and define the utility for consumer type i, where $i \in \{1, \ldots, I\}$, from choosing product k as follows:

$$U_{ik} = \alpha_k - \beta_0 p_k + \beta_i x_k + \epsilon_{ik} = \mu_{ik} + \epsilon_{ik}, \ \forall k \in N, \quad (5)$$

where α_k is the baseline utility that captures the inherent attractiveness of the product, p_k is the price of option k, and ϵ_{ik} is the independent and identically distributed (i.i.d). Gumbel error term that captures uncertainties for which customers have no information from the thumbnail page but realize after a costly inspection. Furthermore, x_k denotes any feature that is "fuzzy" during the search stage but clears upon closer inspection—

Figure 3. (Color online) Shopping Funnel: From the Available Inventory to Assortment Presentation, Formation of Consideration Sets, and Decision to Purchase



Note. The variables Φ_i and Φ_j capture consideration sets for different customer segments i and j who exhibit different tastes and search costs.

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Customers decide which options to click based on slim information in product thumbnails. Importantly, consumers exhibit heterogeneous preferences, that is, type i has unique taste parameter β_i over x_k.

7.2. Fuzzy Features

"Fuzzy" features are not oddities of Despegar—customers confronting fuzzy information in the early stages of the funnel is a common friction seen in most online platforms. The thumbnails of the search results conceal the details of the product. Consider OpenTable in Figure 4 (more examples in Online Appendix O). Customers making restaurant reservations type the neighborhood and cuisine. Then the platform displays hundreds of restaurants and their available timeslots—However, the thumbnail provides fuzzy attributes. Oceans is located somewhere in Union Square, has 1,630 reviews, and prices are "$$$$." All these features are informative but only to some extent. What is the exact address? What do the reviews actually say? What are the prices of the menu? The customer answers these questions upon clicking through to the restaurant page. Here, we learn about the address, the dishes and prices in the menu, the reviews, the hours of operation, and so forth. Consumers who are sensitive (i.e., higher $|\beta_i|$) to price (or location), will be more or less likely to make a reservation once feature "$$$$" (or Union Square) is crystallized.

Customers observe a fuzzy signal θ_k about feature x_k when browsing the thumbnail page (provided in the search results). Based on the fuzzy information, the customer assumes that x_k has probability density function $f_k(x) = f(x|\theta_k)$, with mean $\mathbb{E}(x|\theta_k) = \overline{x}_k$ and support $[x_{ka}, x_{kb}]$. To illustrate: When customers observe that a restaurant has two dollar signs (i.e., "$$"), they assume that prices are within a certain range (e.g., $20–$40); when they observe that a hotel is 2 miles away from the city center, they infer that the hotel location is somewhere on a circle within a 2-mile radius from downtown. (We use a general notation for lower and upper bounds, meaning x_{ka} and x_{kb}, to better capture that "$" and "$$" have different price ranges.) The expected attractiveness for option k is

$$\overline{\mu}_{ik} = \mathbb{E}[\mu_{ik}|\theta_k] = \alpha_k - \beta_0 p_k + \beta_i \int_{x_{ka}}^{x_{kb}} x f_k(x) dx$$
$$= \alpha_k - \beta_0 p_k + \beta_i \overline{x}_k. \tag{6}$$

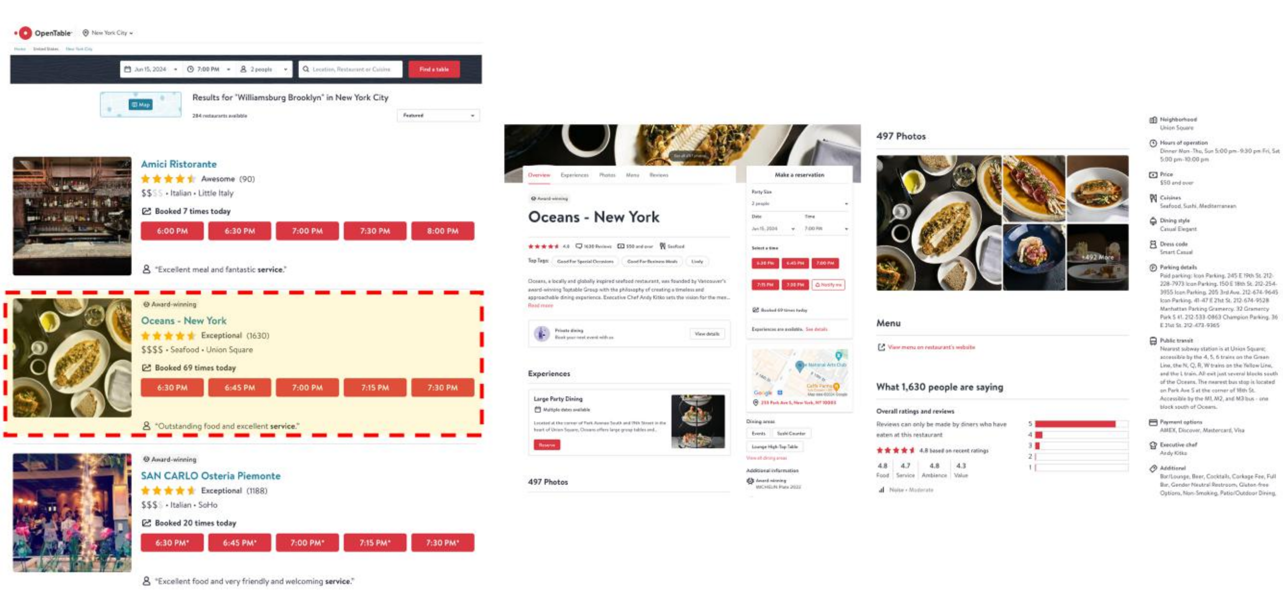
Here $\overline{\mu}_{ik}$ is bounded. Let μ_{lb} and μ_{ub} be the lower and upper bounds of the mean utility, respectively. Thus, $\overline{\mu}_{ik} \in [\mu_{\text{lb}}, \mu_{\text{ub}}]$ $\forall k, i$.

Next, the customer clicks on the product, and arrives to the product page—showing detailed information such as the price points of each dish in the menu, the hotel address, and the review comments. Importantly, any uncertainty surrounding x_k is eliminated: The consumer observes the actual value $\tilde{x}_k$, where $\tilde{x}_k \in [\tilde{x}_{ka}, \tilde{x}_{kb}]$. Notably, the actual support $[\tilde{x}_{ka}, \tilde{x}_{kb}]$ may not necessarily align with the customer's assumption $[x_{ka}, x_{kb}]$. In this context, we define the actual (realized) attractiveness for option k (excluding the realized Gumbel error term) as follows:

$$\mu_{ik} = \alpha_k - \beta_0 p_k + \beta_i \tilde{x}_k. \tag{7}$$

The customer then makes a purchase decision based on the actual product utility shown in Equation (7). Note that customer heterogeneity affects the utility only through β_i, that is, the relative sensitivity to feature x_k. Finally, the outside option is normalized to zero as $U_{i0} = \epsilon_{i0}$. Thus far,

Figure 4. (Color online) OpenTable—Fuzzy Features in Product Thumbnails



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we defined the consumer utility. Next, we discuss the process for the consideration set formation.

7.3. Formation of Consideration Sets

In the *consider stage*, consumer type i browses at a glance the products in the assortment (i.e., the thumbnails in the search results) and forms the expected utility $\overline{\mu}_{ik}$, $\forall k$. The consumer then selects a subset of products for further examination, that is, added to the "consideration set." In the *choose stage*, products included in the consideration set are closely evaluated, and, as a result, the exact value of x_k, together with other unknown features surrounding ϵ_{ik}, are crystallized. Similar to the literature (Hauser and Wernerfelt 1990, Wang and Sahin 2018), we assume that adding products to the consideration set incurs no cost, whereas evaluating each product in the choose stage—which requires processing abundant and more nuanced information—incurs a per-unit search cost. Note that the consumer will only include an additional product if the expected incremental benefit of the added product outweighs the search cost.

Although the costs of sorting each product based on the summarized information displayed in the thumbnails—search results—are negligible, we assume this process could collectively reduce efficiency during the subsequent choose stage due to accumulated search fatigue. This assumption speaks to the findings of Ursu et al. (2023), which provides empirical evidence of accumulated fatigue from online shopping, as seen in consumers frequently taking "breaks" during their search. Indeed, Ursu et al. (2023, p. 111) describes "shopping fatigue" as "the more options a consumer searches, the higher the consumer's search costs per option because of fatigue." In a similar vein, we assume that the more products are displayed in the consider stage, the more costly for customers is to evaluate the actual quality of each product in the choose stage.

The notion of fatigue in the search process due to continuous mental efforts is supported by studies in labor economics and cognitive science (Farber 2008, Chen et al. 2021). For example, Faber et al. (2012) document that humans become less efficient in processing information after continuous work, as longer working hours make them easily distracted and more difficult to maintain focus. We provide a caveat that, although in line with Ursu et al. (2020) we ignore whether such cognitive burden can be moderated via filters, we encourage future research to shed light on the role of various filtering and screening tools.

7.3.1. Search Costs. Consumer type i incurs a search cost, denoted as $c_i(|N|)$, each time an option in the consideration set is evaluated. The search cost is jointly determined by (a) the cardinality of the assortment N, namely $|N|$, and (b) type i's search cost parameter. That is, we allow the search cost $c_i(|N|)$ to vary across customer segments. For instance, segment j may find it easier (less costly) to browse many options, relative to segment i, in which case the corresponding search costs satisfy $c_i(|N|) > c_j(|N|)$. Although in our empirical setting, we exploit heterogeneity in terms of familiarity, varying search costs may originate from other dimensions, for example, relationship tenure, repurchase loyalty, or expertise.

In addition, $c_i(0) = 0$, and $c_i(1) < \log(\exp(\mu_{\text{ub}} - \mu_{\text{lb}}) + 1)$. Intuitively, the search cost is not too high when there is a single product displayed and then at least one product will be added to the consideration set. Finally, we assume $\partial c_i(|N|)/\partial|N| \geq 0$, $i \in \{1, \ldots, I\}$. That is, when faced with a larger assortment, the accumulated fatigue from evaluating more options also increases, thus leading to higher search costs.

Overall, this process reflects that a greater number of alternatives increases "information load" (Scammon 1977)—leading to greater "processing costs" (Shugan 1980) and cognitive "effort" (Johnson and Payne 1985, Chernev 2003b). To summarize: The search cost is moderated by customer segment and is increasing in the displayed assortment size due to higher cognitive burden from forming the expected utility over all the products in the assortment. To the best of our knowledge, we are among the first to incorporate both a behavioral friction in the customer journey and heterogeneity in the search costs.

The consideration set formation ultimately balances the search costs and the product match. The problem can be defined as follows:

$$\Phi_i^N = \arg\max\{\mathbb{E}[Z_i(\hat{N})] - c_i(|N|) \cdot |\hat{N}|, \hat{N} \subseteq N\}, \quad i \in \{1, \ldots, I\}. \tag{8}$$

Here Equation (8) states that the consideration set comprises products that maximize the expected utility of products in this set, net of the total search cost incurred when evaluating each product. More specifically, $Z_i(\hat{N})$ denotes the highest utility of all products for customer type i, that is, $Z_i(\hat{N}) = \max\{U_{ik} : k \in \hat{N}\}$. Meanwhile, the total search cost is determined jointly by $|\hat{N}|$, the number of products to be evaluated in the consideration set, as well as $c_i(|N|)$, the unit search cost, which depends on both the customer type i and the assortment size N.

The consumer ranks products by the expected utility, namely $\overline{\mu}_{ik}$ for all k, and relabels them in decreasing order as $N := \{\kappa_i(1), \kappa_i(2), \ldots, \kappa_i(|N|)\}$. For ease of notation, we define $z_i(N, t) := \{\kappa_i(1), \kappa_i(2), \ldots, \kappa_i(t)\}$. Under this specification, the consumer selects the first t products from N if decides to add t products into the consideration set. Following the result established by Wang and Sahin (2018), we can re-express Equation (8) as follows:

$$t_i^* = \max\{t : t \leq |N|, \mathbb{E}[Z_i(z_i(N,t))] - \mathbb{E}[Z_i(z_i(N,t-1))] \geq c_i(|N|)\}, i \in \{1, \ldots, I\}, \tag{9}$$

and $\Phi_i^N = z_i(N, t_i^*)$. According to Equation (9), the

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consumer sequentially incorporates products that have the highest expected utility among the remaining options into their consideration set, until the marginal gain of including an additional product falls below the per-product search cost $c_i(|N|)$.

Next, we derive our first theoretical result. Specifically, we examine the relative sizes of the consideration sets formed by heterogeneous customers who exhibit varying search costs.

Proposition 1. *Let t_i^* and t_j^* be the number of products in the consideration set for type i and type j customers, respectively. If $|\beta_i - \beta_j| \le \varepsilon$, whereby $0 < \varepsilon < \overline{\varepsilon}$, then there exists $\delta_c > 0$, such that when $c_i(|N|) - c_j(|N|) \ge \delta_c$, then $t_j^* \ge t_i^*$.*

To see this, return to Equation (9), which demonstrates that the consideration set size across customer segments can vary due to heterogeneous search costs and expected product utility. Proposition 1 states that, given the gap between β_i and β_j, the relative size of the consideration sets is primarily determined by the variation in search costs, provided the difference in search costs $c_i(|N|)$ and $c_j(|N|)$ is sufficiently large. In such a case, because $\mathbb{E}[Z_i(z_i(N,t))] - \mathbb{E}[Z_i(z_i(N,t-1))]$ is nonincreasing in t and $c_i(|N|) > c_j(|N|)$, type j customers incurs a less costly search, allowing them to include no less products into their consideration sets than type i customers.

Proposition 1 directly maps Hypothesis 1 in Section 4. If we think of type i and type j through the lens of familiarity with the assortment, we reconcile that the size of the consideration set tends to be smaller (larger) for low-familiarity (high-familiarity) customers. That is, based on the observed disparities in the characteristics of their preferred hotels, and thereby a plausible gap in sensitivity toward fuzzy features, high-familiarity customers form a larger consideration set when their search costs are sufficiently lower than those of low-familiarity customers.

7.4. Choice Model

The consumer forms the consideration set Φ_i^N from the assortment N, and then inspects each option in the *choose stage*. In this stage, the consumer decides which product to purchase following the stylized Multinomial Logit (MNL) model (i.e., we assume the error term ϵ_k in Equation (5) follows i.i.d. Gumbel (0,1)).

7.4.1. Purchase Decision. The consumer gains full insights about the product when clicking-through to the product page. For example, learns about the restaurant's prices or the hotel's reviews. In the choose stage, the consumer makes the purchase decision based on the actual value $\tilde{x}_k$ instead of the expected value $\overline{x}_k$ as in the consider stage. (There is always some "uncertainty" left: We use the words "actual value" as a simplification, although in reality some features will resolve once the consumer actually experiences the product.) Accordingly, the probabilities type i customer buys product k and the outside option are, respectively,

$$\mathbb{P}[\mu_{ik}|\Phi_i^N] = \frac{\exp(\alpha_k - \beta_0 p_k + \beta_i \tilde{x}_k)}{\sum_{l\in\Phi_i^N}\exp(\alpha_l - \beta_0 p_l + \beta_i \tilde{x}_l) + 1},$$

$$\mathbb{P}[\mu_{i0}|\Phi_i^N] = \frac{1}{\sum_{l\in\Phi_i^N}\exp(\alpha_l - \beta_0 p_l + \beta_i \tilde{x}_l) + 1}, \quad (10)$$

where, notably, as customers get to observe $\tilde{x}_k$, the probability of purchase is jointly influenced by the (realized) attractiveness of each product (as expressed by Equation (7)), the number of alternatives in the consideration set (as expressed by Equation (9)), and the specific customer type. However, different from the latent MNL model (Greene and Hensher 2003), customer type is observed in our setting. Given the realized value $\tilde{x}_k$, $\forall k$, we are able to compare the conversion rate under the following conditions.

Lemma 1. *Given two products k and $k' \in \Phi_i^N \cap \Phi_j^N$. If $\beta_i \le \beta_j$, and the realized feature for products k and k′ satisfies $\tilde{x}_k \ge \tilde{x}_{k'}$, then $\mathbb{P}[\mu_{jk}|\Phi_j^N]/\mathbb{P}[\mu_{jk'}|\Phi_j^N] \ge \mathbb{P}[\mu_{ik}|\Phi_i^N]/\mathbb{P}[\mu_{ik'}|\Phi_i^N]$.*

Lemma 1 indicates that when type j customers exhibit greater sensitivity toward the feature that contributes positive utility compared with type i customers (i.e., $0 \le \beta_i \le \beta_j$), then, because product k has a higher realized value than product k' (i.e., $\tilde{x}_k \ge \tilde{x}_{k'}$), type j customers will be more likely to purchase product k over k'. (Naturally, this also holds when type j customers exhibit lower sensitivity to the fuzzy feature that contributes negative utility compared with type i customers, namely $\beta_i \le \beta_j \le 0$.) Once again, β_i and β_j seek to capture heterogeneous sensitivity toward various general features, such as dish prices (food delivery platforms), hotel location (travel platforms), or review comments (online retail platforms).

This theoretical result microfounds Hypothesis 2 in Section 5. We documented that consumers who are more (less) familiar with the city tend to book niche (popular) hotels. The evidence also indicated that niche (popular) hotels are generally more distant (closer) from the top touristic attractions and have fewer (greater) review popularity. It is plausible that high-familiarity customers, who are more knowledgeable about the surroundings, public transportation, and urban amenities, exhibit a milder sensitivity to blockbuster attributes, compared with low-familiarity customers. Specifically, x_k represents the distance from hotel k to a popular city destination, and $\beta_i \le \beta_j \le 0$, with i and j denoting low- and high-familiarity customers, respectively. Thus, Lemma 1 indicates that the relative purchase likelihood for a niche option (k) over a popular option (k') is greater for high-familiarity customers and lower for low-familiarity customers.

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7.5. Impact of Assortment Size on Consideration Sets and Purchases

A behavioral, boundedly rational friction in a consider-then-choose model allowed us to establish two theoretical results: (a) customer heterogeneity moderates the relative size of the consideration set (Proposition 1 → Hypothesis 1), and (b) it drives relative preferences for niche choices versus popular choices (Lemma 1 → Hypothesis 2). Next, we ask the following: How does the assortment size affect consumers' behaviors for the consideration set formation and the conversion rate?

The following result extends Proposition 1 by explicitly studying how the assortment size, in addition to customer heterogeneity, affects the formation of the consideration set.

Proposition 2. *The cardinality of the consideration set for type i customers (t_i^*) does not always increase monotonically in $|N|$. Let t_{i1}^* and t_{i2}^* be the consideration set size formed by type i customers from assortments N_1 and N_2, respectively, where N_2 results from adding a new product to the existing assortment N_1. There exist r_1 and r_2, where $r_1 < r_2$, such that when $|N_1| \le r_1$, $t_{i1}^* \le t_{i2}^*$, and when $|N_1| \ge r_2$, $t_{i1}^* \ge t_{i2}^*$.*

Proposition 2 captures the important behavioral phenomena whereby consumers will not necessarily include more products in the consideration set when additional choices are offered. Importantly, both $c_i(|N|)$ and $Z_i(z_i(N,t))$ are nondecreasing in $|N|$. For example, if the platform expands the assortment breadth with superb quality choices, then the customer will include those products to the consideration set despite the increased search cost. On the other hand, if those newly added products are poor quality, the customer could form a smaller consideration set because the search cost is sensitive to the change in the number of options. In summary, it is the relative tradeoff between the gains of including new options and the increased search costs that determines the size of the consideration set.

It is helpful to consider two stylized scenarios. When the assortment size is relatively small, the corresponding search cost is also low. Thus, the size of the consideration set is bounded by the number of products offered by the platform, namely the assortment size. In this region, we expect the consideration set size to increase with the assortment size. However, when the assortment size is relatively large, search costs become significantly burdensome due to the accumulated fatigue from forming expected utility over a large number of alternatives in the first stage. In this situation, even adding the best option to the menu will not increase the size of the consideration set. That is to say, adding a new product leads to an unchanged or smaller consideration set size.

Proposition 2 generalizes the parameter space covered by Hypothesis 3a. The field experiment showed that a large reduction in the choice menu leads all customer segments to form smaller consideration sets. Proposition 2 demonstrates that this can originate when the reduced search costs do not compensate for the potential utility gain from having more options in the assortment. Intuitively, the (smaller) assortment offered is still relatively large in the eyes of the consumer, regardless of their type, and the (larger) assortment contains abundant options that appear attractive upfront. However, Proposition 2 recovers additional insights: In a different parameter space, reducing the assortment can, in fact, enlarge the size of the consideration set. We might see this overchoice behavior when shrinking the menu makes it substantially easier to decide which options should be clicked on for further examination, thereby reducing subsequent search costs without sacrificing the quality of the consideration set. For example, "Goodreads' Editor's Pick" can simplify the process of discovering relevant and timely books, particularly for customers who are unfamiliar with the genre and may feel overwhelmed by the infinite selection in an online library.

Lastly, we consider the relationship between the assortment size and the likelihood of making a purchase. In the absence of behavioral or informational frictions, conventional wisdom suggests that consumers have better chances to find and buy the ideal match with a larger choice menu (Baumol and Ide 1956). However, we showed that (a) customers experience increasing search costs (or "fatigue") as the choice set gets bigger, and therefore it is unfeasible to examine every single option, and (b) customers rely on fuzzy signals about product features while forming the consideration set based on the search results. As a consequence, changes in the assortment size can impact the conversion rate due to discrepancies in the information related to x_k: between the thumbnail page and the product page, that is, expected $\bar{x}_k$ versus realized $\tilde{x}_k$, respectively.

To understand the underlying mechanism, we introduce the following definitions. For all the products in N, denote the smallest lower bound of support for $\tilde{x}_k$, $\forall k$ as $x_{0a} = \min(\tilde{x}_{1a}, \tilde{x}_{2a}, \ldots, \tilde{x}_{Na})$ and the largest upper bound as $x_{0b} = \max(\tilde{x}_{1b}, \tilde{x}_{2b}, \ldots, \tilde{x}_{Nb})$. Given the assortment N and the respective consideration set Φ_i^N, we further denote $g(\Phi_i^N) = \log(\sum_{l \in \Phi_i^N} e^{(\alpha_l - \beta_0 p_l)})$ as a measure of the deterministic attractiveness from all the products included in the consideration set. Finally, we define $CR(\Phi_i^N) = 1 - \mathbb{P}[\mu_{i0} | \Phi_i^N]$ as customer type i's conversion rate under consideration set Φ_i^N and assortment N. We can derive the following result.

Proposition 3. *Let $\tilde{N}$ be a subset of assortment N. If $|\Phi_i^N| \ge |\Phi_i^{\tilde{N}}|$ and $|\beta_i(x_{0b} - x_{0a})| \le g(\Phi_i^N) - g(\Phi_i^{\tilde{N}})$, then $CR(\Phi_i^N) \ge CR(\Phi_i^{\tilde{N}})$. Otherwise, if $|\Phi_i^N| \ge |\Phi_i^{\tilde{N}}|$ and $|\beta_i(x_{0b} - x_{0a})| > g(\Phi_i^N) - g(\Phi_i^{\tilde{N}})$, then it may occur that $CR(\Phi_i^N) < CR(\Phi_i^{\tilde{N}})$.*

Proposition 3 states that when $|\beta_i(x_{0b} - x_{0a})|$ is sufficiently large—whether due to heightened sensitivity

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(i.e., large $|\beta_i|$) or a wide distribution range of feature x_k (i.e., less informative thumbnail page)—a smaller consideration set might drive a higher conversion rate compared with a larger one. This theoretical result sheds light on the underlying dynamics of choice overload. Note that customers initially rely on fuzzy information on the thumbnail page (e.g., overall product rating, proximity of the restaurant to downtown, or dollar sign) to form their consideration set. Once an option is selected, these fuzzy features are crystallized (e.g., detailed customer reviews, exact location, or full menu), at which point customers make their final purchase decision.

To build intuition for the nuances of choice overload, consider several examples.

7.5.1. Obfuscation. Consider a platform that *obfuscates* feature x_k—That is, there is a broad range between the bounds of $\tilde{x}_k$. We might face such situations when seeing large dollar signs "$$$$" (actual prices can disparately vary across fine-dining restaurants), when reviews are critical beyond the average (comments about elevator access for short-term rentals) or when dish variety for delivery is unclear upfront (the menu reveals vegan-friendly options). It is plausible that consumers add options to their consideration set based on high expected utility, but a closer evaluation unveils that these options are not good ones.

In the context of bookings for short-term rentals, imagine a consumer type i who has a newborn and is sensitive (large $|\beta_i|$) to elevator access (x_k) to carry the stroller. When browsing the search results, the consumer believes that apartment k is a great candidate upfront because its review score is high and so is the expected utility $\overline{\mu}_{ik}$. The consumer wonders, "With this rating, what can go wrong?" Well, upon inspecting the apartment page, learns that previous guests complained about the lack of elevator access ($\tilde{x}_k$ reveals to be low). This decreases the realized attractiveness utility ($\tilde{\mu}_{ik}$) and the consumer refrains from making a purchase. An abundant assortment (and consideration set) size may not lead to higher purchase rates.

7.5.2. Obfuscation and Editor's Pick. Now imagine the platform curates the assortment by removing low-selling apartments, many of which have unfavorable $\tilde{x}_k$. (The platform might believe that a popularity-based Editor's Pick is beneficial, but it is not specifically filtering through x_k.) Consumer type i browses the search results and continues to select options with similarly high review scores (preferences remain unchanged). However, importantly, these curated options tend to exceed the expectations because μ_{ik} is drawn from a distribution favoring higher levels of $\tilde{x}_k$; intuitively, these apartments are collectively more relevant than those considered under the full assortment. This captures the choice overload: consumer type i is more likely to make purchase when she is offered a smaller, more popular choice set.

Interestingly, Proposition 3 allows us to capture the opposite pattern. That is, situations where choice overload is unlikely to arise. Consider a consumer type j, who places little importance on feature x_k (small $|\beta_j|$). This consumer may be indifferent to menu prices, elevator access, markdown promotions, or the distance between a hotel and the opera. Moreover, differences in realized versus expected product attractiveness are not consequential, and thus customers already see what they care about in the early stages in the funnel. Consequently, offering an Editor's Pick actually reduces the likelihood of purchase for those customers, as they would have preferred access to the full choice set rather than a curated selection. In such cases, the platform can extract great value from the long tail.

7.5.3. Transparency. In contrast, consider a platform which embraces radical *transparency*. Here, the noisy information provided on the thumbnail page is not noisy at all; rather, it precisely conveys the feature of interest. For example, the platform might showcase a short immersive video of a restaurant, highlighting the menu, ambiance, and location. As a result, when customers navigate through the search results, they experience little to no uncertainty about x_k: what they see is effectively what they get from the assortment. The difference between the expected $\overline{\mu}_{ik}$ and the realized μ_{ik} is minimal. Therefore, a larger consideration set leads to a higher conversion rate, as the product thumbnails contain all the information customers need to select their favorite choices. In this case, choice overload is also unlikely to occur.

Proposition 3 generalizes Hypothesis 3b in Section 6. In the context of a field experiment whereby the platform reduced the choice set, we documented that low-familiarity customers are more likely to make a purchase, whereas high-familiarity customers are less likely to make a purchase. Return to the Editor's Pick analogy. It is plausible that type i (type j) customers are more (less) sensitive to certain product features that tend to be overweighed by best sellers. When the platform curates the variety by offering the Editor's Pick, it benefits type i customers because the options in their consideration set are more relevant (high μ_{ik}), whereas it harms type j customers because the curated selection excludes their niche preferences. In this context, segments type i and type j stand for low- and high-familiarity customers, respectively.

Notably, Proposition 3 can be extended to situations with M different features on the thumbnail page. That is, $U_{ik} = \alpha_k - \beta_0 p_k + \sum_{m=1}^{M} \beta_{im} x_{km} + \epsilon_{ik}$. The effects of shrinking the choice set on the conversion rate would then depend on comparing $\sum_{m=1}^{M} \beta_{im}(x_{0bm} - x_{0am})$ and $g(\Phi_i^N) - g(\Phi_i^{\tilde{N}})$, where, with a slight abuse of notation,

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x_{0bm} and x_{0am} denote the upper and lower bound for each fuzzy feature x_m.

To summarize, we examined the impact of the assortment size on the formation of consideration sets and the purchase decision. The model microfounds that an assortment reduction can lead to a smaller consideration set (Proposition 2 → Hypothesis 3a) and can lead to flipped changes in the likelihood of making a purchase (Proposition 3 → Hypothesis 3b). We provide a stylized example in Online Appendix Q.

7.6 Numerical Simulations

Finally, we complement Propositions 1–3 through numerical simulations. We consider a platform that shrinks the assortment starting from the least popular options (detailed discussions in Online Appendix R). The intent is to inform customer behaviors across the parameter space, in particular for search costs and for sensitivity to (fuzzy) product features.

The results are summarized in Figure 5. Importantly, we recover three kinds of situations: (a) search costs leading to an inverted U-shape in the consideration set size, (b) choice overload (less is more) when platforms obfuscate the shopping funnel, and (c) the long tail (more is more) when platforms are transparent and features are not fuzzy at all.

8. Discussion and Concluding Remarks

Many shopping decisions can be modeled as a two-stage consider-then-choose process. For instance, platforms offer hundreds or thousands of hotels to choose from in a single city. The information in the search results is too slim to make a decision. To gain insights about each hotel, customers must click on individual options. However, this process is time-consuming and cognitively demanding.

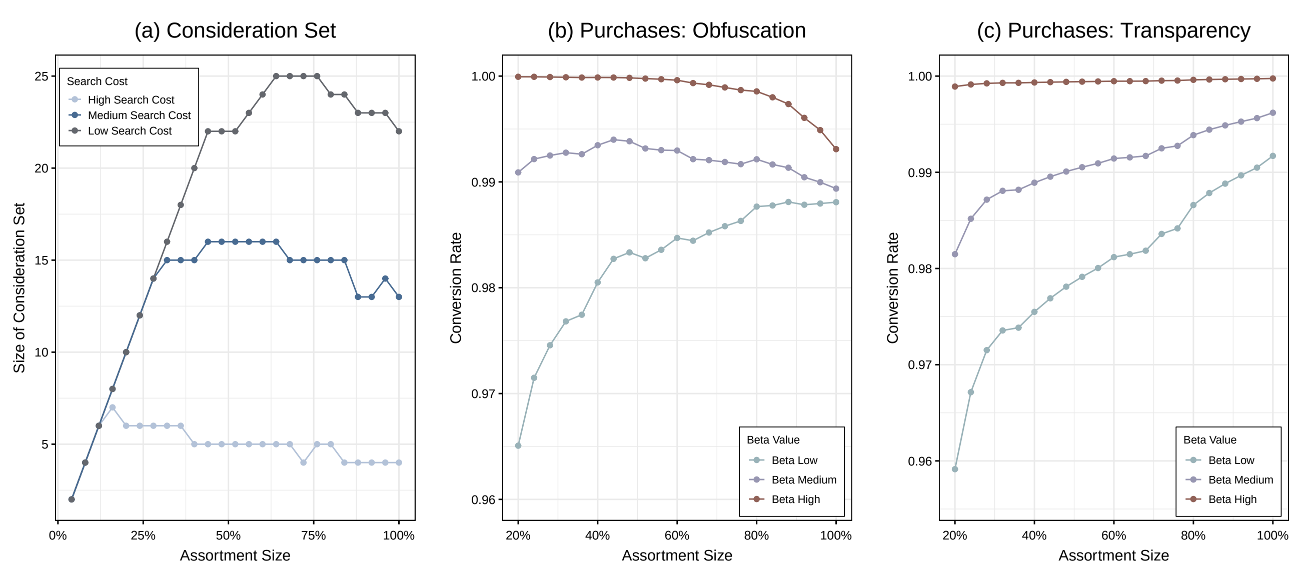
Our empirical analysis in collaboration with a travel platform reveals that customers who are more (less) familiar with the choice domain form larger (smaller) consideration sets and are more likely to purchase niche (best-seller) options. The value of the long tail is fleshed out in a field experiment. Shrinking the choice set yields diverging effects: High-familiarity customers are less likely to make a purchase, whereas low-familiarity customers benefit from a curated menu, increasing their likelihood of making a purchase.

We build a consider-then-choose model to generalize our understanding of shopping frictions in B2C online platforms. We model search costs as a general function of (a) customer heterogeneity and (b) assortment size. Moreover, customers exhibit heterogeneous preferences for product attributes. Our theoretical results explain differences in the size of consideration sets across customer segments. Additionally, the effects of expanding the assortment breadth on the consideration set size can be ambiguous, as it simultaneously leads to higher search costs and a greater number of potentially high-quality options to choose from. For instance, removing options with high ex ante but low ex post attractiveness can lead to a smaller consideration set. Importantly, this can boost the purchase probability—choice overload effect—especially for customers who are relatively more sensitive to fuzzy product attributes.

8.1. Managerial Implications

Booking hotels is a high stakes and difficult decision for most customers—The price point is meaningful, and there are uncertainties about picking the “right hotel,” respectively. Thus, understanding pain point frictions that

Figure 5. (Color online) Consideration Set Size and Conversion Rate Under Various Assortment Reduction Rates



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emerge in the shopping journey is critical. The average conversion rate in online retailers is between 2% and 5%. Lifting the purchase rate by one percentage point to half a million users during 30 days, at an average $250 price, represents an additional $1.25 million in hotel gross bookings. Therefore, the effects that we observe in click-through and conversion rates are economically impactful.

Determining the right assortment size is a recurring challenge for platforms. On one hand, customers have heterogeneous preferences, so expanding the variety increases the chances of a good match. On the other hand, too many options can overwhelm customers—Search costs prevent them from examining all options. To address this, online platforms employ advanced ranking algorithms (Ursu 2018, Donnelly et al. 2023). However, our findings reveal that platforms should (a) *customize* the assortment size or rotate the variety (Ramdas 2003) and (b) avoid standardizing assortment cuts because there is a market for the long tail. Instead, assortment planning could be tailored to customer heterogeneity, inferred from historical browsing patterns, enabling customers to better compare options and find the ideal choice.

The insights from our research are applicable across online platforms, extending beyond the realm of online travel, such as Amazon, Airbnb, Grubhub, and OpenTable. Our research empirically and theoretically demonstrates that behavioral frictions interact with customer heterogeneity, significantly influencing click-through rates and purchase rates. Furthermore, we show that a curated assortment—for example, Editor's Pick—can effectively reduce uncertainty and increase purchase rates for some customers. However, it can backfire for customers who either undervalue best-selling options or exhibit preferences for niche attributes.

The reader might note that this presents a challenge for the platform: Although offering a more customized assortment has clear benefits, the question remains—how can this be effectively achieved? Said differently, what features are essential for creating an "Editor's Pick"? A thorough understanding begins by embracing taste heterogeneity. Instead of applying one-size fits-all heuristics—for example, prioritizing best sellers—platforms must recognize the nuances in customer preferences, behaviors, and their decision-making processes. Similarly, platforms may want to consider the tradeoff between true variety (spectrum of niche tastes) versus repetition (me-too, overly similar products).

8.2. Limitations and Future Research

Our data lacks covariates at the consumer level, time spent examining each option, the sequential filters applied to screen out options, and the order in which each option was added to the consideration set and analyzed. These limitations are opportunities for future research to capture richer dynamics in consider-then-choose decisions. For example, it would be interesting to utilize consumer-level data and employ latent class MNL in the choice stage to capture both observed and unobserved heterogeneity. Meanwhile, future work could test moderating effects of familiarity on the pairwise consumer-hotel distance or on the polarization of hotel reviews. It would also be interesting to experimentally test the interplay between filtering, assortment size, and information processing. Additionally, our field experiment was designed at the consumer level, but the assortment reduction was not tailored to each consumer. For example, platforms can redefine sets of low sellers and best sellers by customer segments. The theoretical and empirical findings in this work encourage scholars to test boundary conditions by testing ranges of assortment reduction rates, as well as by customizing online assortments in real time based on user queries.

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