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# Peer Priming? A Large-Scale Field Experiment Studying the Impact of Popular Rankings on Demand in Mobile Retail

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### **Presenter Information**

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# Peer Priming? A Large-Scale Field Experiment Studying the Impact of Popular Rankings on Demand in Mobile Retail

*Completed Research Paper*

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## Abstract

*Consumers on mobile retail apps face significant search costs due to the small screen size of devices. One of the search aid features to improve the search convenience is to show consumers a small set of frequently used searches conducted by peer consumers on the platform as a prime cue. We refer to this feature as the popular ranking search aid (PRSA). Collaborating with Meituan, a leading services mobile app in China, we implement a large-scale field experiment to explore how PRSA affects consumer search activities and purchases. Our analyses generate three key findings. First, PRSA leads to an increase of 18.6% in page views and a 6.4% increase in purchases. Second, the change in shopping behavior emerges through a change in search behavior with more non-directed searches and fewer directed searches. Third, our mediation analysis supports that search behavior mediates the business outcomes. We offer theoretical and managerial implications.*

**Keywords:** Mobile Shopping, Popular Ranking, Customer Search, Field Experiment

## Introduction

As mobile devices become increasingly central to online retail activities, the search costs imposed on consumers as they maneuver through the mobile interfaces are non-trivial (Lee et al. 2020; Son et al. 2020). Two major reasons exist for why these costs are relatively high – *first*, compared to traditional retail, mobile-based retail platforms typically incorporate a much wider product assortment. For instance, Amazon provides access to 9.7 million sellers worldwide with over 12 million products and services (Dayton 2022), through their mobile applications. Similarly, Meituan, the largest local service mobile app in Asia, accommodates 8.3 million merchants with 43.6 million orders placed per day, primarily through the mobile channel (DMR 2022). *Second*, the smaller screen size and limitations on information display modalities affect how easily consumers can navigate through the platform’s offerings (Dellaert and Häubl 2012; Ghose et al. 2013). Even expert consumers can struggle in finding new products or services through mobile devices, given the limitations of the physical form factor (Lee et al. 2020).

In recognition of these costs imposed on consumers, retail platforms have introduced several technological tools that help guide consumers in their purchase journey. These include online recommendation systems provided on specific product pages, collaborative filtering systems that allow peer-to-peer cross-selling, haptic and notification techniques that allow specific products to be made salient to the consumer, location-based targeted promotion techniques that use the consumers' location to highlight specific products, and so on. These technologies, however, are based on helping consumers once a specific set of products or services have been identified, since they require some information on consumer preferences and requirements *ex ante*. However, a first step towards reducing search costs may indeed be based on enhancing the initial search process itself. This forms the broad research question we address in this paper – *how can the search process be enhanced from a consumer perspective to generate positive outcomes for both consumers and retailers on the mobile channel?*

Prior work in marketing suggests that consumers go through four stages in a shopping journey - need identification, information search, browsing and alternative evaluation, and purchase (Kotler 2002). Within this shopping journey, the search process in particular helps consumers filter out irrelevant information, allowing them to focus on the required product or merchant (Moe 2003; Park et al. 2020). Thus, enhancing the search process can be beneficial for consumers, especially when presented with large product assortments on small screens. Research (Fan et al. 2005; Feng et al. 2007) has largely focused on enhancing the fit between the consumer-provided search terms and the possible products or services that fit with these terms – indeed, search engines are based on maximizing retrieval based on user-issued search terms. But can the search terms used by consumers themselves be influenced in a way to enhance outcomes?

As a potential solution to this question, platforms have recently started rolling out a simple crowd-sourced approach to enhancing the search process early in the purchase funnel by providing consumers with a set of popular search terms that are drawn from peer consumers in almost real-time. This functionality, referred to as *popular ranking search aid* (PRSA), provides a list of the most frequently used search terms on the platform at the point in time when the consumer initiates a search (Lambrecht et al. 2018). Through a combination of *priming* that enhances *salience* (Higgins 1996), the PRSA can influence how the user's search process unfolds at an early stage, rather than at the later point when recommendation systems or location-based techniques kick in. Furthermore, the technology is relatively easily implemented since it simply reflects the overall search behavior exhibited by *all* consumers, rather than based on selecting subsets of consumers with similar preferences or attributes, a process that is computationally expensive in real time while also requiring specific customer data.

Interestingly, some platforms have incorporated PRSA-like functionality as part of their search processes in recent years. Taobao, the largest e-commerce platform in China, launched a PRSA-like functionality in early 2019, providing a list of the top searched topics by peer customers on the search page when the customers go to the search bar (36kr 2019). Lazada, the leading mobile commerce company in Southeast Asia, started providing a similar service in 2020 to help shoppers with cues for shopping. Beyond retail, platforms like Twitter have introduced similar “trending topic” features to help users explore content in late 2019 (Cruze 2020) while Netflix started to roll out a list of the daily most-streamed genres in early 2020 to help viewers explore different types of content (Escandon 2020). The presence of this functionality raises an unexplored question – how does the presence of the PRSA affect the efficacy of the search process, in terms of actual product views and purchases made by the consumer? This would be evident if consumers exposed to the PRSA actually end up with viewing and purchasing more products. To test for these effects, we collaborated with Meituan, a leading services mobile app in China, to conduct a randomized field experiment wherein a randomly selected set of shoppers were provided with a PRSA implemented on the search page for a period of 30 days in December 2021.<sup>1</sup> Specifically, the functionality was implemented on the site relevant to food ordering and provided “treated” shoppers on the search page with a set of 10 most popular dish genres searched by peers before they entered in any search queries. Our proprietary dataset thus consists of 25,921 Meituan shoppers in the treatment group, matched to 26,563 shoppers in a control group selected from the two cities in China where the experiment was conducted. Our experimental data are based on aggregate purchase and search behavior of shoppers over a 30-day period, where identification is provided by randomization. Noted that our analyses on the search activities only focus on manual search queries that shoppers type the search term at the search bar, and the clicks and purchases we calculated are

<sup>1</sup> We use the terms ‘shoppers’ and ‘consumers’ interchangeably in this paper.

based on these manual searches. Thus, we provide a conservative estimation of the PRSA impact without counting clicks and purchases through the clickable text of the top 10 most popular genres.

Our baseline results, show that the presence of the PRSA increases the efficacy of the search process significantly – on average, shoppers in the treatment group increase their views of specific restaurant pages by 18.6% and purchase 6.4% more meals, relative to the control group. Effectively, by priming shoppers who arrive at the search page in search of food options through displaying a set of “popular” options, the platform is able to achieve clearly better economic outcomes for both the platform as well as the consumer. We delve deeper into our dataset to understand what specific search-related behaviors are modified when the PRSA is provided, and in doing so, we identify interesting and relevant mediating variables that drive search behavior.

Consumers use the search functionality in two distinct ways. First, they use *directed* search, wherein customers search for a specific keyword related to a merchant or stock-keeping unit (SKU) (Moe 2003). Directed search occurs when shoppers are clear about the specific food category or product they are interested in, leading to a narrow consideration set and homogenous search results. Alternatively, consumers also engage in *nondirected* search, where a non-specific keyword related to a generic list of merchants or product genre is used (De et al. 2010; Moe 2003). The search results thus vary across various features (e.g., brand, type, price), requiring consumers to conduct additional exploration before making the final purchase decision (Cox and Rich 1964; Janiszewski 1998). Interestingly, our analysis shows that while the presence of the PRSA increases total searches on the mobile app by 41.6% relative to the control group, there is an *increase* of 62.7% in *nondirected* search volume while *directed* search volume *reduces* by 4.5%, suggesting that the priming cues provided through the generic topics provide search convenience and direct shoppers’ attention to more exploratory search. The PRSA thus induces a shift towards nondirected, open-ended searches while reducing directed searches, which then leads to higher views and purchases on product pages. From a theoretical viewpoint, we thus explicate a mediation model: the effect of the PRSA on purchases and views is *mediated* by changes in search behavior, characterized by the proportion of directed to nondirected searches. Statistical tests confirm the observed mediation, showing the specific pathways by which the PRSA induces shopping outcomes.

Our work here makes two significant contributions to extant research in IS. First, much of the current work (Lee and Hosanagar 2019; Li et al. 2020; Li et al. 2022) seeking to enhance mobile-based retail performance is aimed at the product or service page, or at targeting individuals based on their specific characteristics. Recommendation systems, for instance, are based on either individual or product features. Similarly, promotions and mobile-based interventions are aimed at the point of feature evaluation or purchase. However, research aimed at enhancing the start of the search process itself remains scarce. Our work is focused not on the downstream effects of the search process, where recommendation systems and contextual targeting is used, but directly at the search task itself, through the provision of a simple and inexpensive aggregate decision tool. Using a simple priming exercise, we show that showing consumers crowdsourced, peer information on popular searches can generate significant value. We do not discount the value of downstream technologies like recommendation systems; rather, we show how modifying the search process itself can yield relatively high dividends.

Second, we explicate the process of search itself by identifying directed and nondirected search behavior, and the mediating influences of these variables on outcomes. The distinctions between directed and nondirected search have not been clearly enunciated in the current literature on mobile commerce. Our analysis showing the diverging effects of the PRSA on the search process itself allows us to theorize about how priming can affect the business value of mobile retail technologies. The mediated model we propose here can be used as a starting point for a richer theoretical development on how customer decision-making progresses on mobile devices.

From a managerial viewpoint, our work shows the economic value attached to a simple tool that uses crowdsourced data to enhance the search process. As policy makers enforce more strict data protection for customer privacy (e.g., policies like the GDPR in Europe), it becomes costly for managers to collect individual data to design personalized recommendation or targeting systems (Sun et al. 2022). Furthermore, these systems are computationally relatively costly and complex. Our experiment shows how a simple heuristic can provide value. While we focus our work on the food delivery sector where consumers are faced with a significant range of choices that induce search costs, the value of priming search is easily generalizable to other mobile-based retail contexts as well. Interestingly, at our research site, the PRSA was

quickly extended to the full platform on the conclusion of our experiment, speaking to the value and efficacy of this simple functionality.

## Background Theory

### *The Use of Customer Support Technologies in Mobile Retail*

It is well-accepted these days that a significant proportion of retail sales, whether in products or services, is conducted on mobile devices. As product lines offered by retailers and services have increased multifold, the search and transaction costs associated with smaller screen sizes and limited functionalities on mobile devices have also increased commensurately. As a response to these higher search and transaction costs in the mobile ecosystem, a series of innovations have emerged in the last two decades that are aimed at enhancing the product search and discovery process for consumers seeking the ideal product or service. Most of these technologies are based on reducing search costs, enhancing the abilities of customers and platforms to identify suitable prices, product and service types, as well as helping manage promotions, prices and uncertainties associated with mobile shopping (Ghose 2018). Extant work has shown, across a multitude of papers, that these technologies add clear economic value to both consumers and retailers alike.

An early innovation in enhancing mobile retail was the search tools made available by all retailers (Dukes and Liu 2016). Aimed at the early stages of the purchasing funnel, search tools are critical in allowing the consumer to narrow down the search to the most appropriate and suitable products (Peterson and Merino 2003). Beyond search per se, a significant source of innovation within the retail context has been the development of recommendation systems (RS) (Kumar and Hosanagar 2019; Lee et al. 2020; Xiao and Benbasat 2007). RS, seen typically at the product page, allow the consumer to consider alternative products that are similar to the focal product, thereby enabling demand smoothing as well as the serendipitous discovery of new products that may be a better fit for the consumer. By modeling consumers' interest and analyzing historical purchase activities, RS help consumers gather information and learn about new products (Resnick and Varian 1997), thus altering shoppers' consideration set during the purchase process (Li et al. 2022). Recent work shows that RS generate significant economic value for retailers as well as consumers (Kumar and Hosanagar 2019) and in particular, through the mobile channel (Lee et al. 2020). The specific algorithms used within these systems have undergone significant innovation over time as well, leading to their enhanced efficacy (Adomavicius et al. 2021).

Beyond RS, recent research has also studied how mobile technologies can be used for dynamic marketing and promotion campaigns, thanks to the ubiquitous presence of smartphones and their intensely personal nature (Melumad and Pham 2020). The adoption of mobile apps, increasingly common within the retail sector, has been shown to enhance purchasing behaviors, thanks to the ease of use and reduced search costs (Narang and Shankar 2019). Mobile app adoption also helps retailers roll out mobile-specific loyalty programs that are easier to manage and more effective (Son et al. 2020). Additionally, mobile devices can be used in a context-aware manner to send promotions and discount information to consumers selectively, depending on their prior purchase histories or current locations (Andrews et al. 2016; Fang et al. 2015). A combination of contextual characteristics such as commute route, weather, location, and movement trajectory, that are potentially visible through mobile phones can be used to optimally drive shopping decisions (Ghose et al. 2019b). Specific haptic and visual functionalities implemented on mobile devices (Melumad et al. 2020), in addition to simpler functionalities like push notifications and SMS messaging (Lee et al. 2020), allow many opportunities for retailers and consumers to find ways to enhance the mobile shopping experience beyond what was possible several years ago.

In summary, the literature has seen significant work on the development of various applications and technologies aimed at enhancing the retail experience on smartphones (Melumad et al. 2020). These technologies utilize the various modalities and software agents that are bundled into smartphone operating systems, as well as access to large streams of data made available through customer sales and search data, location-based systems, access to real-time environmental data such as weather and traffic, and so on. Within the typical purchase funnel, these technologies are aimed at the downstream stages of consideration set formation, alternative evaluation, purchase and post-purchase stages rather than the search stage per se (Kotler 2002). Furthermore, these technologies are complex, require large amounts of real-time data, and are computationally costly, while also presenting privacy challenges (Adomavicius et al. 2021; Jiang et al. 2021). Interestingly, the original search process, captured in the ubiquitous search bar, has remained

largely unchanged (Peterson and Merino 2003).<sup>2</sup> It is exactly this stage of the search process that is the focus of our work, as discussed next.

### ***The Search Function and Its Utility***

The primary function of the search feature within retail platforms is to offer consumers a direct way to search for a set of relevant products and services, thereby allowing them to narrow down the potential set of alternatives into a smaller consideration set (Moe 2003). As the shopping journey progresses, the consumer transits through the subsequent elements of the purchase funnel, finally leading to purchase (Kotler 2002). The search bar thus is instrumental in establishing the start of this purchase journey, and the manner in which information is provided could affect both the breadth and depth of search behavior displayed by the consumer (Dukes and Liu 2016). Recent work shows that over 43% of mobile shoppers use the search function to explore and find what they want (Algolia 2019).

In general, consumers rely on two sources of information when they search for products or services on a retail platform. First, they rely on internal information and mental models of the product or service space to construct appropriate search terms – these internal models are shaped by previous interactions with the market and the relevant product space (Boothby et al. 2014; De et al. 2010). To the extent that consumers can construct these search terms efficiently and accurately, the search process is likely to provide relevant items for their consideration. However, this process can also be prone to recall bias and is limited by the consumer’s recall abilities. Second, search can be guided by external information cues provided by the retail site in various ways, such as through advertisements, promotional material, targeted messages based on prior purchases, and recommendation systems (Honka et al. 2017; Li et al. 2022). However, as mentioned above, providing information through recommender systems, promotions and advertising represents significant costs. We consider an alternative source of information provided to consumers facing a search task in the retail context that is significantly cheaper to generate – the popular ranking search aid (PRSA).

The PRSA, in its simplest form, represents information that is drawn from the market in a seamless and unfiltered manner, capturing the most frequent search categories or search terms that have been used by others on the platform. The information generated through the PRSA incorporates two key factors - wisdom of crowd and recency, since the actual information shown is based on the most frequent and recent searches conducted by peers on the platform. Note that depending on the context, aggregate search information can be provided on multiple levels within the retail platform – at the product level, category level, or retailer level. For instance, the PRSA can generate a list of the most common product searches (“Levi Strauss jeans”), categories (“Fast Food”, “Comedy”) or retailers (“Best Buy”, “Zara”), depending on the context. Which level is implemented remains a design parameter for the platform owner.

Computationally, the PRSA is inexpensive to generate since it simply aggregates information across time and customers. Unlike typical RS, the PRSA is generated at the search page, representing the “wisdom of the crowd” indirectly. Furthermore, the PRSA can be tailored to provide information on product search or category search, depending on the implementation, while functionalities like RS and context-based targeting are largely based on specific products. Finally, the PRSA provides aggregate data from peer searches with no relevance to the focal shopper’s interests, differentiating it from the personalization and customization needed for RS and targeted promotions. Thus, advanced algorithms that rely on large amounts of customer and product data needed to process personalized recommendations or promotions are not required, thereby mitigating potential privacy concerns as well.

These advantages notwithstanding, it is not clear that providing the PRSA to consumers will result in positive sales outcomes. Showing aggregate search trends from others may not satisfy the focal consumer’s specific requirements (Bart et al. 2014; Goldfarb and Tucker 2011), especially when hyper-customization is the desired goal within large-scale retail markets. There is no guarantee that the focal consumer’s requirements are correlated with aggregate peer trends that are displayed by the PRSA, potentially causing a disruption in the consumer’s cognitive processes with negative outcomes on sales (Everard and Galletta

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<sup>2</sup> Newer developments in AI-enabled search (such as the new Bing search agent) may change this status quo but at the time of our study, these were still unavailable in the market.

2005). Prior work in priming and salience suggests, however, that there is an argument for the positive influence of PRSA on sales; we discuss these arguments in the next section.

### ***The PRSA as a Priming Factor***

Search on retail platforms typically starts with the consumer's internal mental representation of the product space, as discussed above. When consumers try to construct a series of keywords or search terms for a product or service, they largely rely on information encoded in their memory (Higgins 1996; Molden 2014). However, only a small portion of memory is typically accessible during the search process (Sharit et al. 2008). Even when this information is accessed, the appropriate search terms suitable to the context at hand may not be easily accessible. It is here exactly that priming can work to enable a more effective search process. Defined as the activation of particular associations in memory before a specific action is taken (Higgins et al. 1982), priming activates previously stored schema to access information stored in memory (Mandel and Johnson 2002). To the extent this information is available but not salient and easily recalled, priming allows it to be brought into salience and therefore, actionable by the user.

Appropriate primes can be generated through technology artifacts in two distinct ways (Boothby et al. 2014). First, primes provided through the technology artifact can highlight and make salient specific aspects and features of the market, making it easier for consumers to process the required information for search (Meyers-Levy 1989). Thus, when shown a multi-dimensional prime, consumers are more likely to recall multiple aspects of a decision-making problem while single-dimensional primes tend to invoke individual dimensions (Chen et al. 2018). Similarly, providing concrete or abstract primes can influence observers by generating concrete or abstract responses to a problem domain (Freitas et al. 2004). In an open-ended problem setting, applying particular forms of technology-enabled primes can help enhance the salience of specific forms of information, and thereby influence downstream behavior appropriately.

In addition to enhancing salience, the PRSA can also facilitate *categorical priming*, whereby individuals are more likely to display action that remains categorically within the same category that is shown in the prime (Herr 1986). When shown a prime that is associated with a specific category of action or phenomenon, individuals tend to make judgments and decisions based on these recent primed categories (Herr 1989). Thus, Burtch et al. (2015) show how readers who are primed by privacy concerns are more likely to display privacy concerns in their crowdfunding choices. Similarly, in the context of a Q&A site, readers are more likely to respond to a concrete question as a prime with a concrete answer, versus a more abstract answer (Peng et al. 2020).

Thus, we argue that the information on peer search trends displayed by the PRSA is likely to influence consumers who are at the search bar and starting the search process. In cases where consumers are relatively undecided about their specific product or service requirements, displaying the most commonly searched categories of products through the PRSA is likely to induce the focal consumer to consider adopting one of these categories, narrowing down search parameters within that category. Alternatively, in cases where the consumer arrives at the search bar with a specific choice in mind, here again the frequent search categories displayed by the PRSA is likely to induce some change in behavior by invoking categories or products that the consumer may not have fully remembered. In either of these cases, we expect that the search process will be influenced by the provision of the PRSA at the retail search bar. Whether the PRSA leads to higher sales, i.e., whether the search process is successful in resulting in a sale, remains an open empirical question which we test using a field experiment, as described in the next section.

## **Experimental Design and Empirical Analysis**

### ***Research Site and Setting***

Our experiment on the performance implications of the PRSA were conducted in collaboration with Meituan, the largest local life service mobile app in China. Meituan, established in 2010, currently hosts retail services in four main sectors – food delivery, offline services flash groceries, and hotels. The platform has over 8.3 million merchants. As of 2021, Meituan recorded 691 million shoppers and achieved RMB 179.1 billion (USD 26.76 billion) in revenue (ChinaInternetWatch 2022). Within the platform, food delivery services remain the largest revenue driver with 14.4 billion transactions in 2021, generating RMB 96.3 billion in revenue. Given the focus on food delivery, we focus our field experiment on this sector of the retail

service. Meituan reports that shoppers conduct over 1 billion daily searches using the search bar provided on the Meituan mobile app, leading to 40% of all transactions.<sup>3</sup> The search process on the app consists of three steps. First, shoppers tab to the search bar at the top of the app interface to initiate a search. This takes them to a separate search page where they are required to type in their specific queries, representing the second step. Third, the system returns a list of relevant products or merchants on the results page, where shoppers can then click a specific merchant to view the detailed products and services provided by the merchant. Our experimental stimuli are located within these three specific steps that encompass search.

## Experimental Design

Our field experiment was developed in collaboration with the Meituan search engineers whose main responsibility is to optimize and improve the shopper search experience on the app. The design of the PRSA was developed in conjunction with app designers to ensure that the new functionality could be seamlessly integrated into the existing app. After the PRSA functionality had been tested within the firm, the field experiment was launched on December 18<sup>th</sup>, 2021 for a period of 30 days, during which the PRSA was implemented for the food delivery process across both the iOS and Android Meituan apps. To minimize interruptions to the existing service, the experiment was implemented on a random selection of Meituan shoppers from two major cities in China. Within each city, a small random selection of users was selected as the treatment group, whereby they were given access to the PRSA on their app. These users were exposed to the PRSA every time they tabbed to the search page during the experiment period. Within each city, we were able to generate a random set of control shoppers to match the treatment group, allowing us to identify the causal impact of PRSA. Our final sample thus consisted of 25,921 shoppers in the treatment group, with a control group of 26,563 shoppers. Subsequent analysis was conducted using the dataset composed of these shoppers.

The PRSA was implemented as an add-on information display at the second step in the search process for all shoppers of the treatment group. We show a visual illustration example in Figure 1. As shown on the left panel of Figure 1, shoppers in the control group saw the status quo app interface *without* the PRSA feature display. By contrast, shoppers in the treatment group saw an added section of the locally popular dish genres searched by the peer on the search page (right panel of Figure 1) every time before typing a search query. To suit the specific domain here (food delivery services), the PRSA was designed at the category level rather than the individual merchant level. It incorporated state-of-the-art deep learning neural network that interpreted the search intent of customers from the utilized keywords and generalized the topic from individual keyword searches to categories. The locally sourced trendy topics from peer searchers were ranked, based on search volume, and updated to the list displayed on the PRSA to the mobile user. The displayed frequency rankings were updated every two days so that shoppers in the treatment condition within a city saw the same list of popular categories, regardless of their own shopping preferences. During the experiment period, the PRSA only summarized searches related to food and beverage categories.



**Figure 1. Experimental Design (Visual Illustration)**

<sup>3</sup> <https://blog.51cto.com/51ctoeditor/2372856>

## Data and Randomization Checks

At the conclusion of the experimental period, the research site provided us with de-identified proprietary data from system search logs and transaction databases for each shopper throughout the experiment period. The combined dataset has detailed records for individual shoppers' search activities, and subsequent browsing actions (i.e., clicks on the merchant page representing views), as well as purchases made through the search result page. Noted that we exclude the search, click, and purchase activities initiated through clicking any text link on PRSA or recommended merchants at any other part of the app. Thus, our focus is on shoppers' manual search queries under the search function and subsequent clicks and purchases on the app. Using this dataset, we are able to fully capture the downstream behavior of users coming from the search page, as well as identify their total views of individual merchants and purchases that emerged from their search activities specifically.<sup>4</sup> We were also provided some demographic data on each shopper, including the range of their ages, marital status, education level, growth (active usage level), and Meituan shopping loyalty membership level.

An important consideration in creating this dataset pertains to evaluating the specific search terms used by a shopper in terms of the intent of the shopper: i.e., did the shopper intend to search for a general category / genre or a specific merchant / product? Meituan's search engineers use a combination of Nature Machine Translation (NMT) and a Bidirectional Encoder Representations from Transformers (BERT) framework to understand search intent from the search terms. The returned information includes a list of related merchants and products on the results page, which is presented to the shoppers. Given the large size of the training data available to the firm, their internal statistics suggest that their analytical framework is able to generate accuracy of roughly 94%. While the technical details of this framework are outside the scope of our work here, they are provided upon requests. Essentially, this framework allows us to also categorize each search query by intent, which we will consider in our empirical extension section later in the paper.

We conduct our analysis on aggregated search, browsing and purchase data for each individual shopper across the 30-day experimental period, so as to simplify the analysis. Due to page constraints, we do not report the summary statistics here. The summary statistics for the dataset show that the majority of our experimental subjects are single and possess either bachelor's or master's degrees. The average shopper conducted 141.27 searches and viewed a product/service page 18.72 times. Each shopper completed an order 1.88 times, displaying a view to purchase ratio that is line with prior work in the retail sector (Lee et al. 2020). Note that all cases where purchases came from the shopper directly going to the merchant's page, i.e., where the search page was bypassed, have been omitted since these are outside the scope of this project. As is common with field experiments (Bapna et al. 2016; Sun et al. 2019), we conduct randomization checks, i.e. comparing the means of key demographic and dependent variables before the experiment across the treated and control groups.<sup>5</sup> The results in Table 1 show no statistical difference between the control and treatment groups on any of the demographic or dependent variables during the pre-treatment period, speaking to the integrity of the randomization process.

Variable	Variable Definition	Treated group	Control group	t-statistic	p-value
Marriage	0: Single 1: Married	0.447 (0.077)	0.358 (0.069)	-1.109	0.270
Age	1: <20 2: 20-25 ... 6: >40	3.556 (0.008)	3.547 (0.008)	-0.803	0.421

<sup>4</sup> We exclude shoppers' clicks on PRSA ranked topics in our analyses since these are intermediate outcomes rather than clicks on merchant pages. Instead, we use these click behaviors to evaluate the treatment significance level as part of manipulation checks.

<sup>5</sup> Randomization checks were conducted on a pre-treatment period of 15 days. Therefore, the total number of searches, views, and purchases are roughly half of those reported in Table 1. We proportionally adjust the volume of views and purchases to avoid disclosing the sensitive business information of our research partner.

MemberLevel	1-7 based on the total amount spent on the platform. 1 is the lowest and 7 is the highest membership level	3.915 (0.008)	3.907 (0.008)	-0.596	0.550
Growth	1-8 based on the active usage on the platform. 1 is the lowest and 8 is the highest growth level	3.924 (0.008)	3.917 (0.008)	-0.525	0.559
Education	0: under the bachelor degree 1: bachelor and higher degree	0.860 (0.002)	0.836 (0.002)	-0.921	0.356
TS	Number of total searches	59.434 (0.720)	59.418 (0.808)	-0.014	0.988
DS	Number of directed searches	15.569 (0.202)	15.644 (0.231)	0.244	0.806
NDS	Number of nondirected searches	43.865 (0.559)	43.773 (0.616)	-0.109	0.912
TV	Number of total views	8.989 (0.121)	9.685 (0.506)	1.318	0.187
TP	Number of total purchases	0.851 (0.011)	0.949 (0.082)	1.163	0.244
<b>Table 1. Randomization Checks</b>					

## Empirical Analysis

We start with testing for the treatment effects of the PRSA on the total views and purchases made by shoppers in our experimental period. One of the primary objectives of the experiment is to understand how the PRSA can help prime shoppers and affect their downstream behavior. Therefore, we propose:

$$DV_i = \beta_{10} + \beta_{11}PRSA_i + \beta_{12}X_i + \sigma_i, \quad (1)$$

where  $DV_i$  represents the set of dependent variables measuring shopper  $i$ 's behaviors on the platform - the total number of views (measured by page clicks) of shopper  $i$  on the search result page within the experiment period, as well as total number of purchases (orders) made by shopper  $i$  in the same period of time.  $X_i$  includes the vector of additional control variables - age range, marital status, education, Meituan membership and growth level.  $PRSA_i$  captures the treatment, with 1 if shopper  $i$  is in the treated group and 0 otherwise. Lastly,  $\sigma_i$  is the heteroscedasticity-robust standard error. We estimate the model using OLS, given the clean identification provided by the field experiment. The results are shown in Table 2.

Columns (1) and (2) report the impact of the PRSA on shopper's views of individual merchant pages through the search activities. The coefficient of  $PRSA$  is 3.859 ( $p < 0.01$ ), showing that shoppers exposed to the PRSA generate 3.859 more views of merchant pages relative to those in the control group. In Column 2, we report the effects for Log (TV) to account for potential non-linearities in our dataset, which is common in retail data. The results show that exposure to the PRSA lifts the total number of views by 18.6% ( $100 \times (e^{0.171} - 1) \%$ ). More interestingly, Columns (3) and (4) show that how exposure to the PRSA influences actual purchases. The positive coefficient of  $PRSA$  (0.339) in Column (3) indicates that shoppers who are exposed to the PRSA place more orders for food delivery, relative to those in the control group. From Column (4), we note that the PRSA enhances customer purchases by 6.4% ( $100 \times (e^{0.062} - 1) \%$ ), which is a non-trivial increase in total sales for the platform.

One potential concern in our analysis thus far is that the PRSA is implemented only at the search page. Therefore, unless the shopper went to the search page, they would not otherwise observe anything different in the app. It may be argued that the identified effect is driven by a small proportion of active shoppers. However, this problem does not seem severe here, since 63.6% of the shoppers in the treatment group used the search page at least once during our experimental period. In further robustness, we also consider alternative regression specifications for our analysis. Since page views and purchases are count variables, we estimate Negative Binomial and Poisson regression models and find fully consistent results with these specifications as well. These results are available upon request from the authors.

To examine if the increase in views and purchases is linked to actual searches, we also conduct a similar analysis to check if the total number of searches conducted by a shopper increases as a function of exposure to the PRSA. Therefore, we use total searches as the dependent variable, with the results shown in Columns (5) and (6). As is observed, shoppers exposed to the treatment conduct more searches relative to the control group (3.748,  $p < 0.05$ ), thanks to the priming effect provided by the PRSA. From Column (6), we show that the PRSA enhances customer searches by 41.6% ( $100 \times (e^{0.348} - 1) \%$ ). Given the higher volume of searches through the PRSA treatment, it perhaps follows that views and purchases on merchants would be higher. However, to fully understand how search behavior change as a result of the treatment, we conduct a more detailed analysis of individual search behavior ex-post, described next.

Variables	(1) TV	(2) log(TV)	(3) TP	(4) log(TP)	(5) TS	(6) log(TS)
PRSA	3.859*** (0.165)	0.171*** (0.008)	0.339*** (0.022)	0.062*** (0.006)	3.748** (1.817)	0.348*** (0.127)
Controls	Y	Y	Y	Y	Y	Y
Observations	52,484	52,484	52,484	52,484	52,484	52,484
R-squared	0.066	0.075	0.017	0.026	0.087	0.134

Note. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . Robust standard errors are reported in parentheses.

**Table 2. Impact of PRSA on Total Number of Views, Purchases and Searches**

### ***Empirical Extensions – Directed and Nondirected Search***

In characterizing search behavior in a more granular manner, we consider the two kinds of searches that are typically observed in retail contexts – *directed search* and *nondirected search* (De et al. 2010, Moe 2003). As described earlier, directed search typically entails the use of specific search queries that lead to a result list of particular merchants or SKUs (Moe 2003). Directed search narrows the consideration set for shoppers as the search result generates a homogeneous list of products or services. Using such narrow and targeted search parameters limits information made available to the shopper since it reduces exploration, serendipitous discovery and consequently, reduces the probability of purchase if the results do not satisfy the original search requirements (Popielarz 1967; Schlosser et al. 2006). In contrast, nondirected search involves the use of search queries that are nonspecific, and related to a generic set of merchants, categories, or product genres (De et al. 2010; Moe 2003). Nondirected search thus results in a more diverse set of information being presented to the shopper, with a broad set of relevant products and services (De et al. 2010). These products are heterogeneous across various features, such as brand, type, price, and segment, requiring shoppers to invest more effort in explorative actions before making the purchase decision (Cox and Rich 1964; Janiszewski 1998). Given a vast product line and the potential for serendipitous discovery, nondirected search is arguably more likely to provide suitable choices to the consumer, and enhance the odds of a purchase, all else being equal.

Empirically, most shoppers utilize a combination of directed and nondirected searches as they navigate retail platforms (Moe 2003). In cases where there is a history of prior purchases and the shopper has clear preferences over the product line, directed (concrete) searches may be useful and effective rather than the open-ended nature of nondirected searches. However, in contexts where preferences are not clearly specified or purchasing is driven by impulse, nondirected search is more effective. In the present case, when presented with the PRSA and the categories that are shown, the shopper is more likely to be categorically primed (Herr 1989), leading to a greater probability of nondirected searches. Interestingly, even shoppers invoking the retail app with a clearcut intention to order a specific product may, on viewing the options provided by the PRSA, be nudged into considering an alternative category, leading to more nondirected searches. The heterogeneous choices provided as a result, even potentially under the same generic category (Moe 2003) could lead to less recall effort on the part of the shopper, and higher odds of eventual purchase.

Summarizing these arguments, we contend that in the presence of the PRSA, the shopper is more likely to use nondirected searches rather than directed searches, on average. Furthermore, the use of increased nondirected searches are likely to result in a higher number of views and product purchases, relative to the control group where no priming information is provided. We thus propose that the effect of the PRSA on

views and purchases, shown in Table 3, is theoretically *mediated* by the type of searches that are induced. In other words, the PRSA changes the ratio of directed to nondirected searches observed in the focal shopper, which leads to the higher views and sales empirically estimated above. We test this proposed mediating relationship below.

### Tests for Mediation

The first step in mediation testing involves identifying directed and nondirected searches within our dataset. Given the BERT framework available to Meituan’s engineers and the large corpus of available data, the search intent behind each query can be accurately estimated with 94% accuracy. This infrastructure can categorize each search query into a directed search that relates to an exact merchant name or an SKU of products (e.g., McDonald’s or Big Mac), as well as a nondirected search leading to a list of merchant types or product genres (fast food or burger). We use this framework to separate out the directed and nondirected searches for each shopper in our dataset. Subsequently, we first analyze the impact of the PRSA treatment on the number of directed and nondirected searches, using the same specification as Equation (1). The results are shown in Table 3.

As evident, the effect of the PRSA on nondirected searches is significant and positive, as shown in Columns (1) and (2). The coefficient value of PRSA in Column (1) is 4.679 ( $p < 0.01$ ); shoppers exposed to the PRSA perform 4.679 more nondirected search activities than those in the control group. Specifically, the coefficient of the logged dependent variable in Column (2) indicates that the PRSA drives shopper nondirected search by 62.7% ( $100 \times (e^{0.487} - 1) \%$ ). In contrast, the impact of the PRSA on nondirected searches, shown in Columns (3) and (4), is negative ( $-1.209$ ,  $p < 0.05$ ). The coefficient in Column (4) suggests that shoppers exposed to the PRSA perform fewer directed searches by 14.5% ( $100 \times (1 - e^{-0.157}) \%$ ). Additionally, the positive and statistically significant coefficient in Column (5) shows that the *ratio* of nondirected to directed search (*Rate NDS*) increases 11 percent points, indicating that the increase in overall search volume attributed to the PRSA is driven by increased nondirected searches.

Variables	(1) NDS	(2) log(NDS)	(3) DS	(4) log(DS)	(5) RateNDS
PRSA	4.679*** (1.499)	0.487*** (0.114)	-1.209** (0.511)	-0.157** (0.078)	0.110*** (0.001)
Controls	Y	Y	Y	Y	Y
Observations	52,484	52,484	52,484	52,484	52,484
R-squared	0.078	0.126	0.077	0.125	0.059

Note: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . Robust standard errors are reported in parentheses.

**Table 3. Impact of PRSA on Shoppers’ Mobile Search**

As a second step to analyzing mediation (Baron and Kenny 1986), we consider how the volume of directed and nondirected searches conducted by a shopper are associated with product views and purchases. We separate product views and purchases that emerged from directed and nondirected searches in our dataset and conduct a split-sample analysis based on the specification shown in Equation (1), across the two types of searches. In almost all cases in our data, it is possible to separate out the purchases and product views that emerged from either a directed search or a nondirected search that preceded it because we ensured that the product views and purchases that are included emerged from a clear directed or nondirected search process that was registered immediately prior to the view or purchase. Here again, we compare the control group to the treatment group in terms of the number of directed searches that lead to product views / purchases. The results of these contrasts are shown in Table 4.

The coefficients in Section A, Columns (1) and (4) show contrasting coefficient signs, indicating that compared to the control group, the treatment group (with PRSA = 1) shows a lower frequency of views initiated by directed searches, but a higher frequency of views driven by nondirected searches. In effect, the results indicate that when shoppers treated with the PRSA shift to more nondirected searches relative to directed searches, the resulting number of product views actually increase. In other words, the incremental gain in product views associated with the PRSA comes via the increased use of nondirected searches, and a concomitant reduction in directed searches, relative to the control group. A similar trend is observed with

purchases as well in Section B of Table 5, where the lower use of directed search and a higher use of nondirected search, attributable to the PRSA treatment, leads to higher views and purchases.

Section A	(1) Views-DS	(2) log(Views-DS)	(3) Views-NDS	(4) log(Views-NDS)
PRSA	-0.520** (0.212)	-0.021*** (0.011)	4.619*** (0.321)	0.174*** (0.011)
Controls	Y	Y	Y	Y
Observations	52,484	52,484	52,484	52,484
R-squared	0.054	0.107	0.053	0.116
Section B	(1) Purchases-DS	(2) log(Purchases-DS)	(3) Purchases-NDS	(4) log(Purchases-NDS)
PRSA	-0.091** (0.042)	-0.013*** (0.007)	0.365*** (0.079)	0.063*** (0.009)
Controls	Y	Y	Y	Y
Observations	52,484	52,484	52,484	52,484
R-squared	0.009	0.014	0.017	0.025

Note. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ . Robust standard errors are reported in parentheses.

**Table 4. Breakdown Analysis for Effect of PRSA on Shopper Views and Purchases**

While these individual results from Tables 3 and 4 show evidence for how the PRSA's effect on views and purchases is mediated by the changing pattern of directed to nondirected searches, we can test for mediation more directly using mediation analyses with bootstrapping methods provided by Hicks and Tingley (2011) and Imai et al. (2011, recently used by Li et al. (2022)). We use the “*medeff*” package in Stata, where a default 1000 simulations are selected for bootstrapping the coefficients and standard errors. We use the PRSA treatment as the independent variable, the volume of searches conducted by a focal shopper as the continuous mediator, and product views and purchases as continuous outcome variables.

Due to page constraints, we do not report the results here and the results are available upon requests. The direct path from the PRSA treatment to total number of searches is positive and significant (3.748,  $p < 0.01$ ) while the path from the total number of searches to product views is also significant (0.038,  $p < 0.01$ ). More importantly, we see that the average causal mediated path, i.e., the average effect of the PRSA treatment on product views acting through an increase in total number of searches, is 0.142 and significantly different from zero, representing 3.7% of the total effect generated by the PRSA treatment. In effect, we show the presence of a causal mediated effect of the PRSA treatment on product views, mediated by the total number of searches utilized by the focal shopper. Consistent results are viewed with respect to total purchases as well – the effect of the PRSA on total purchases increases through the mediated path of total searches (average causal mediation effect = 0.012).

As expected, the direct effect of the PRSA treatment on the nondirected search volume is significant and positive (4.679,  $p < 0.01$ ), as is the effect on product views (4.113,  $p < 0.01$ ). Moreover, the average causal mediation effect of the PRSA treatment, through nondirected search volume, on product views is 0.510, representing 11.10% of the total effect of the treatment on product views. A similar effect is observed with purchases from nondirected searches – the average causal mediation effect is 0.083, representing 22.7% of total effect of the PRSA on final purchases made by the average shopper.

Finally, in the case of directed searches, we see divergence from the mediation results viewed above. As argued earlier, the PRSA treatment tends to drive consumers away from increase the use of nondirected search rather than directed search. Thus, compared to the control group, the effect of the treatment on the number of directed searches is negative and significant (-1.210,  $p < 0.01$ ). However, while the directed effect of the treatment on product views is insignificant, the effect through the mediated pathway is negative and significant; the average mediated effect is -0.340, representing 64.3% of the effect of the treatment on views. Thus, we see almost complete mediation in this case, through the pathway of reduced directed search

volume. Similar results are observed with purchases as well – the average mediated effect is negative and significant ( $-0.033$ ), representing 35% of the effect of the PRSA on product purchases, showing almost complete mediation. In effect, the PRSA negatively affects the use of directed searches and thereby, has a negative mediated effect on product sales and views.

In summary, our analysis suggests three clear inferences. First, the priming effect created by the PRSA has a positive effect on product views and purchases, relative to the control group, as shown by our experiment. Second, through causal mediation modeling, the change in search behavior is a significant factor in generating the observed effect of the PRSA on product views and purchases. Finally, the PRSA actually helps shift searches from directed searches to nondirected searches, where a larger and more heterogeneous set of choices are provided to the shopper, thereby leading to a higher number of views and products. We essentially provide evidence for a mediated model of the PRSA treatment on outcomes, where the mediating causal effect works through an increase in nondirected searches and the reduced use of directed searches.

In this paragraph, we aim to provide more clarifications in order to rule out two potential alternative explanations threatening to our proposed mechanism. First, one may postulate that PRSA provides is a pure search convenience because shoppers could click on the text link on the list and explore related merchants and products. Our analyses rule out this explanation as we only focus on manual search queries shoppers' type in the search function and the subsequent clicks and purchases initiated from these search activities. Thus, our identified effect on search behavior change is a priming effect of PRSA in affecting shoppers' search intent with non-directed search terms. Second, one may concern that the identified effects on clicks and purchases are driven by the result availability of different types of searches. For instance, directed search could lead to limited search results with fewer options whereas non-directed search engenders more results for shopper choice. While we do not have data access to the search results for a particular search, the management team shared with us that in major Chinese cities, there are numerous merchants providing the same dish and it is a very rare case that a shopper finds limited options in the search result. Even if the shopper might search a very particular merchant, the app applies algorithms to generate related merchants serving the same dish in the result page to increase the options. Thus, we believe that it is very unlikely that the effects are driven by the availability of search results.

## Discussion and Conclusion

The search process on mobile-based retail remains an important step in the shopping journey for most consumers, even in the presence of advanced technological features such as recommendation systems and context-aware location-based services (Lee and Hosanagar 2021; Li et al. 2022; Luo et al. 2014). Most shoppers continue to use the search tabs on mobile apps, regardless of how clearly formed their ex-ante requirements are. Therefore, it is not surprising that retail platforms continue to invest in decision support tools that can enhance the efficacy of the search process itself (Fan et al. 2005). The work we report here is thus based on a collaboration with Meituan wherein we study the implementation of a simple, crowd-based search aid that helps prime shoppers as they look for food delivery options through the search page. Using a field experiment conducted over 30 days in two cities in China, we show that exposure to the PRSA leads to an increase of 18.6% in the views of merchant pages on the platform, as well as an increase of 6.4% in purchases through the platform, providing ample evidence of the return on investment on this simple technology. Our work here does not invalidate the need for other technologies like recommendation systems and location-based services but acts as a clear complement to these by targeting an earlier stage of the consumer shopping funnel – the search process.

In order to understand why we see this effect on product purchases and views, we delve deeper into actual search behaviors in our context. Interestingly, we note that the priming effect induced by the PRSA has distinctly diverging effects on the extent to which shoppers use directed versus nondirected search on the platform. We find that the PRSA promotes nondirected search activities by 4.9% while lowers directed search activities by 1.5%, indicating that priming shoppers with a broad category-based set of suggestions has the effect of inducing more open-ended search behavior. This open-ended search behavior tends to throw up a more heterogeneous set of options, which in turn enhances the odds that a successful purchase is made. Thus, we provide evidence for a clear mediated relationship between the PRSA prime and product views and purchases – the volume of directed versus non-directed search being the mediating variable. Providing information through the PRSA does not make non-directed or directed search more effective per se – the conversion rate of searches does not vary between the control and treatment group. Rather, we see

that the PRSA simply changes the ratio of the two types of searches for the average shopper, thereby yielding incrementally higher product views and purchases.

Our findings are helpful in informing managers of mobile-based retail platforms in terms of how they may be able to enhance the shopping experience for shoppers, while improving their own revenues (Alba et al. 1997; Rowley 2000). As a first step, improving the shopper search experience on mobile devices is critical to the success of mobile commerce. In particular, ensuring that consumers are not constrained by the physical form factor of mobile devices requires managers to be creative in terms of how they can develop technological aids (Häubl and Trifts 2000). The design and implementation of the PRSA is simple and inexpensive, relative to other technological options, and therefore represents an easy win (Andrews et al. 2016; Resnick and Varian 1997). Additionally, to the extent that nondirected searches appear to be more effective in generating purchases than directed searches, managers should consider how a combination of the PRSA and the higher proportion of non-directed searches can be leveraged to enhance value for shoppers. These insights are particularly important for food delivery apps since shoppers using mobile devices usually have a short lead time from information search to actual purchase (Ba et al. 2022). Given limited cognitive resources and patience observed in such settings, even simple tools like the PRSA can allow for more exploration and better outcomes for all parties concerned.

Our work here also highlights some theoretical contributions to extant IS research on technologies focused on the demand side of mobile commerce, such as RS and personalization (Kumar and Hosanagar 2019; Lee and Hosanagar 2021). Recommendation systems are based on directing demand along similarity of products or users, with the hope that search costs can be eased through serendipity and salience. Alternatively, promotion techniques that rely on traffic, congestion, and location rely on temporal salience and short-term responses to local stimuli (Ghose et al. 2019a; Luo et al. 2014). Techniques such as push notifications and app-based haptic reminders are based on nudges. All of these are based on specific sets of products and services that are targeted, using information already available about the shopper and her preferences. In contrast, the PRSA uses simple primes that are targeted at effectively triggering the shopper's mental representation of the product or service space, aimed at broad categories rather than specific merchants. From a theoretical perspective, therefore, our work opens up avenues for future research where simple and computationally easy priming techniques may be used at early stages of the retail purchase process to guide shopper behavior (Kotler 2002). While the design of the PRSA we use is simple and static, one can envision ways in which even these static primes can be enhanced through selective customization as well as extended to other categories or types of purchases.

As an example, future research could create simple primes using specific subcategories of products or services, based on combining some broad location-based or customer-based information (Fang et al. 2015; Luo et al. 2014). Similarly, while we use a frequency-based scheme in designing the PRSA, it is possible to seamlessly mix high-frequency and low-frequency categories in the PRSA as a way to direct demand serendipitously, similar to recommendation systems but with much computational power needed. Furthermore, we consider the food delivery context here, where the cognitive resources expended by the average shopper is not very high. However, priming through the PRSA could also work in contexts like fashion retail apparel, where popularity among peers provided even at the broad category level, could be highly influential. In the context of experience goods, for instance, peer behavior is typically quite influential (Lee et al. 2015; Liu et al. 2016). In such settings, PRSA-like functionality may display a particularly high efficacy, which explains why platforms like Netflix have implemented similar functionality. Our work thus opens up many potential areas where PRSA-like functionality, implemented early in the search process, may render significant positive ROI.

Our work here is also subject to certain limitations, which we discuss here. First, our experimental context limits us to test the effect for only one search aid system design based on popular rankings. As mentioned above, more work is needed in alternative settings to fully understand how these technologies are influential in driving search and purchase behaviors (Li et al. 2022; Zhang et al. 2019). Second, we only observe shopper click and purchase activities, but do not have information about post-purchase satisfaction. Though the PRSA might improve the search experience and drive more purchases, it could also end up with a negative impact on shopper satisfaction if a nondirected search leads to an unsatisfied product purchase, which represents a topic for future research. Third, our empirical conclusions are based on data analyses from one mobile app and one particular context; future work is needed to establish the generalizability of

our results. Finally, we consider a relatively short period in our study (30 days). The long-term implications of these technologies remain compelling but will need further analysis.

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