The Information Billboard: Effects of Popular Search Terms on Search Behaviors and Digital Divide

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Abstract

Popular search terms (PSTs), which provide real-time access to frequently searched terms, have been instrumental in saving time and reducing search costs for information seekers. Recently, a major search engine in Korea abruptly discontinued its PSTs feature. This study examines the impact of this termination on search behaviors, specifically among information-poor individuals such as the elderly, the poor, low-income earners, and those with lower education levels. Using unique panel datasets reflecting search engine app usage, we employed reduced-form approaches to comprehensively analyze the effects of this policy change on digital divide in forms of information disparity across diverse social groups. The removal of PSTs generally discouraged user engagement in searches. Of greater concern is the asymmetric effect of discontinuation based on socioeconomic status, as disadvantaged users experienced significantly increased search costs. These underprivileged users were less able to effectively utilize alternative search venues compared to their more privileged counterparts.

Keywords: Popular Search Terms, Information Inequality, Digital Divide, Mobile Apps, Difference-in-Differences.

1. Introduction

For several decades, search term-based search engines have served as essential gatekeeping conduits through which users find valuable information and discover numerous websites and mobile apps of genuine interest at low search costs. Notwithstanding these benefits, however, controversies continue to exercise the minds of IS researchers as to whether these innovative artifacts exacerbate or ameliorate information inequalities among diverse users who may vary with respect to Internet skills in general and search skills in particular (Robinson, 2009). Given variations in search skills, search engines may continue to inadvertently divide the information rich and the information poor—a phenomenon that may worsen commensurate with advancements in search technologies.

The debate over the information inequality driven by search engines is further fueled by the recent rise and fall of the powerful information-search features offered by major search engines. Popular search terms (PSTs) or search trends (e.g., Google's Trends, Yahoo's Trending Now, Baidu's Top Search Keywords, and Naver's Real-Time Popular Search Terms) have facilitated the effortless and rapid identification of and access to the most searched rising search words. These services display a list of popular search terms (typically 10 to 20 items) that are extensively searched by users at the time of search entry and update them dynamically to maintain recency (Figure 1).

Figure 1. Examples of PSTs

Although these technologies have provided information seekers with an assortment of functional benefits, such as convenience and low search costs, these advantages come at a price: Users only passively consume information that mirrors others' interests and preferences rather than actively generate content in the form of search terms, that is, content that reflects their own occupations, preferences, and views. Alternatively, PSTs may provide, through rising popular search terms, easy access to distinct categories of useful recent information that would otherwise have gone unnoticed, thereby promoting informational diversity among social groups at minimum search costs.

Amid inconsistent evaluations and interpretations, little effort has been extended to a scholarly probing of how PSTs affect individuals' search behaviors and information-seeking propensities. This deficiency motivates the current research, which attends primarily to the heterogeneous effects of PSTs on social groups that diverge with respect to age, education level, occupation (blue-/white-collar work), and income—factors that have often been considered reflective of Internet usage and search skills (Martin and Robinson, 2007). Drawing on the literature on the digital divide, we assumed that individuals' search skills are highly associated with their Internet use. Therefore, socially disadvantaged groups are assumed to have lower search skills than their counterparts.

Along this line of inquiry, we explore the following questions: To what extent does the discontinuation of PSTs affect search frequency and duration at a focal search app? In response to the PSTs abolition, which app categories (i.e., news, SNSs, communication, and finance) do users leverage as an alternative source of information? Are there any variations with respect to the use of such substitutes depending on search skills? Finally, how does the termination of PSTs affect information inequality among users with different societal characteristics?

Our data provide an ideal setting, as they were obtained from a major search engine in Korea that discontinued its PSTs services amid public backlash in February 2021. We collected a large volume of data on individual mobile actions that reflect numerous users' search behaviors on a focal search engine app before and after the termination of the PSTs service. The data also contain the key demographic information of individual users (age, education level, income, etc.). On the basis of these unique resources, we employed a difference-in-difference (DID) approach as a causal estimation strategy to identify the effects of PSTs on search behaviors and their heterogeneous effects on diverse social groups, and the effects of PSTs on the overall mobile behavior.

A preview of the findings indicated that individual users substantially reduced their total search duration as well as per visit duration at the focal search engine after the PSTs service was halted. This result implies that PST termination may discourage users from proactively engaging in searches. Further analysis revealed that old people incurred sharp increases in search costs as measured by duration per visit after the shock, but no such change occurred among their younger counterparts. Likewise, users with lower levels of education and lower incomes incurred higher search costs relative to those with higher education and higher earnings after the cessation of the PSTs service. Our findings generally suggest that popular searches, such as PSTs, can level the playing field for search minorities. On the basis of these results, we drew useful managerial and policy-related implications for how PSTs features affect information inequality among diverse social groups.

2. Related Literature

Our study builds upon and expands the existing body of literature on the digital divide (e.g., DiMaggio and Hargittai 2001; Van Dijk 2020), which has had a profound effect on the welfare of individuals, societies, and countries. This form of inequality has been defined in terms of its range and scope in several research strands, but it generally refers to the growing gap between individuals who have the access and capability to use digital technologies (i.e., computers and the Internet) and those who do not. Studies (e.g., Akhter 2003, Haigh et al. 2014) have also identified numerous sociodemographic characteristics that widen the divide, including age, gender, race, income, and education and have explored its effects on underprivileged members of society, especially poor, less educated, and elderly populations.

Earlier IS studies on the digital divide (e.g., Dewan and Riggins 2005; Chinn and Fairlie 2006; Dewan et al. 2010) concentrated exclusively on identifying the drivers of broadening technological inequality between developed and developing countries. Although such research continues to evolve, scholarly attention in the IS field has shifted to the effects of the gap on individual users. Agarwal et al. (2009), for instance, demonstrated that peer effects and social interactions, in addition to demographic factors, are associated with variations in Internet use among individuals. Wei et al. (2011) conceptualized the notion of the digital divide among individuals as occurring on three levels, namely, *access*, *capability*, and *outcome*. The digital access divide denotes the inequality in access to digital knowledge and infrastructures. The digital capability divide is the inequality in individual capability to leverage and exploit digital technologies because of differences in access to such resources and other contextual factors. Finally, the digital outcome divide refers to the inequality in outcomes (e.g., skill, productivity, job opportunities) due to variations in individuals' digital capabilities.

The authors used social cognitive theory (i.e., self-efficacy; Bandura 1997) as a basis for providing a rich theoretical account of the digital divide, with assessment directed to the dynamic relationships among the aforementioned levels.

Focusing on the digital inequality between the socioeconomically advantaged and disadvantaged (SEA and SED, respectively), Hsieh et al. (2011) found that differences in these populations' motivations and conditions with respect to social, economic, and cultural capital contribute to the disparity. Most other studies devoted efforts to illuminating the digital divide through differences in the adoption and use of hardware infrastructures (i.e., PCs and Internet), but Viard and Economides (2015) explored the role that digital *content* plays in such inequality. They uncovered that "software" (i.e., content) can influence adoption more heavily than hardware depending on the economic and demographic conditions of countries and markets. Lutz (2019) articulated how and under what circumstances digital inequalities evolve and expand in the age of artificial intelligence, the Internet of Things, and social media. Their findings suggested that the digital divide intensifies particularly during disasters and emergency situations, thus penalizing the underprivileged.

Deviating from the abovementioned tendencies in extant scholarship, the current research centers on the information inequalities driven by variations in search and information-retrieval skills among diverse social groups. The gaps in information retrieval and know-how have emerged and expanded among various social groups who differ in information-seeking and cognitive abilities (Wilson et al. 2003; Lorigo et al. 2006). For this reason, we are motivated to investigate the heterogeneous effects of trend search features, taking heed of the social division that arises from imbalanced information access.

3. Data and Variables

In order to conduct an empirical investigation, we utilized a comprehensive dataset consisting of panel data that captures the usage patterns of mobile applications by users over a period of time. This unique dataset was obtained from Nielsen KoreanClick, which employs a stratified sampling method based on diverse demographic factors to ensure the representation of the country's population. Previous studies by Kwon et al. (2016) and Han et al. (2016) have utilized this dataset. The data regarding individual app consumption was collected through a tracking application, which recorded the frequency and duration (measured in seconds) per week of app usage for each user's installed apps. Specifically, the dataset provided information on the weekly app usage behaviors of 1,788 Android users, encompassing a total of 42,824 distinct mobile apps classified into 13 pre-defined categories that are subdivided into 71 sub-categories as established by the company. Additionally, demographic characteristics of the participants were obtained and included in our analyses.

The focal search engine company abruptly discontinued the PSTs service on February 25, 2021 — the day the external shock occurred. In our DID setting, the main research window was set at 12 weeks before and after the shock (November 30, 2020, to May 16, 2021). We employed four measures as the dependent variables (Table 1); *Search_Duration* denotes the total time spent per week on the focal search app after activation, where *Search_Visit* indicates the number of times the app was visited per week. *Search_Duration_per_Visit* refers to the time spent on each visit, which has been frequently used as a proxy for

Table 1. Variable description and statistics

Variables	Descriptions	Mean	SD	Min	Max
$Search\ Duration_{i,t}$	Time spent (in minutes) by panel *i* on the focal Search app at week *t*	127.707	223.485	0	3139.550
$Search\ Visit_{i,t}$	Panel *i*'s number of visits to the focal search app at week *t*	44.731	103.036	0	3656
$Search\ Duration\ per\ Visit_{i,t}$	Time spent (in minutes) by panel *i* on each visit to the focal search app at week *t*	2.507	3.915	0	194.846
$Search\ Share_{i,t}$	The percentage of time spent by panel *i* on the focal search app versus total mobile app usage at week *t*	0.063	0.102	0	0. 977
$Total\ Duration_{i,t}$	Total time spent by panel *i* on mobile apps at week *t*	2262.680	1388.160	0.067	11194.817
$Total\ Visit_{i,t}$	Panel *i*'s total number of visits to mobile apps at week *t*	1280.490	1238.050	0	22135

Note. The descriptive statistics are based on the raw data, which comprised 1,788 panels spanning 24 weeks. Observations for all variables are equal to 42,912 measuring users' search costs (Goutam and Dwivedi, 2012). The longer the search duration per visit, the higher the search costs incurred. Finally, *Search_Share* represents the percentage of time spent on the focal search app out of the total time consumed on all the apps installed on a user's device at week *t*. For additional analyses, we measured Total Duration and Total Visit, which represent the total time spent on all the mobile apps installed on the device and the total number of visits made to such apps, respectively.

4. Analysis of Search Behavior

4.1. Difference-in-Difference (DID) Setting and Propensity Score Matching (PSM)

To accurately estimate the causal effects driven by the PSTs cancellation through the quasi-experiment setting of DID, control and treatment groups were defined on the basis of the following manner: Although the shock occurred to the focal company, its rival maintained its policy throughout the study period despite movement by the former. The users of the focal company were thus assigned to the treatment group, and those of the rival engine constituted the control group. Note that users occasionally leverage multiple search engines but return to a dominant one for routine search tasks. Accordingly, a user was included in the treatment group if he/she used the focal company as the main search engine for over 80% of his/her total search time (measured in seconds). Conversely, a consumer was assigned to the control group if he/she used the focal engine for less than 20% of such duration (measured in seconds). The results remained quantitatively unchanged when alternative threshold values (i.e., over 90%) were adopted.

A potential concern with respect to this classification is that the treatment and control groups may differ systematically in their propensity to choose the focal engine as their principal search app. To alleviate this concern, we carried out propensity score matching (PSM) to ensure that no discernable difference existed between the two groups in terms of the observables before the shock (Rosenbaum and Rubin 1983). We employed sociodemographic (age, gender, occupation, residential district, education, income level, and marital status) and behavioral usage variables that reflected the users' total mobile usage, their internet search usage, and the number of distinct apps used. We adopt one-to-one nearest-neighbor matching, from which 372 paired

Table 2. Matching performance and balance checks

Variables	Before Matching			After Matching		
	Mean Control (n=401)	Mean Treated (n=1,029)	p-value	Mean Control (n=372)	Mean Treated (n=372)	p-value
Total App Usage Duration	2168.830	2279.597	0.030	2177.698	2101.315	0.959
Total App Visit Counts	1064.291	1269	0.000	1098.903	1077.874	0.565
Duration of Search App Use	135.567	198.468	0.000	144.766	155.496	0.088
Visit Counts of Search App	39.263	64.271	0.000	42.715	46.422	0.114
Number of Apps Used	34.780	41.256	0.000	35.883	37.743	0.325
Number of App Categories Used	8.165	8.883	0.000	8.300	8.527	0.313
Ratio of Male (%)	59.6	41.7	0.000	57.3	51.9	0.162
Ratio of Teenagers (%)	0.7	1.4	0.425	0.8	0.8	1.000
Ratio of 20s30s (%)	11.2	22.4	0.000	12.1	11.0	0.731
Ratio of 40s50s (%)	56.9	57.9	0.760	58.1	58.3	1.000
Ratio of 60s70s (%)	31.2	18.3	0.000	29.0	29.8	0.872
Ratio of Office Job (%)	38.9	38.2	0.851	38.7	37.1	0.700
Ratio of Living in Capital City (%)	46.9	45.0	0.559	44.9	45.4	0.941
Ratio of University-Graduated (%)	69.8	66.6	0.264	68.8	66.9	0.638
Ratio of High Income (%)	35.4	38.2	0.360	35.8	38.7	0.448
Ratio of Married (%)	77.8	76.3	0.589	76.9	82.3	0.084

Note. "Ratio of High Income" refers to the percentage of individuals earning over 5 million KRW within the group. The unit of duration variables is minute.

users were identified. All the covariates were statistically balanced after the matching (Table 2).

4.2. Effects of PSTs Termination on Search App Usage

We conducted a DID analysis using the matched data derived through PSM. In our DID specification, β in Equation (1) compares changes in the treatment group's weekly usage time on the focal search app after the discontinuation of the PSTs structure with those occurring in the control group.

$$\begin{aligned} &FocalSearchAppUsage_{it} \\ &\quad = \alpha + \beta * Treat_i * After_t \\ &\quad + \mu_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

Here, $Treat_i$ is a binary variable that represents the treatment group, and $After_t$ is an indicator of whether week t falls in the post-period (after the shock). We included two-way fixed effects μ_i and δ_t to control for the unobserved individual- and week-specific confounders, respectively. We implemented DID regression against the four dependent variables (Table 3).

The first and second columns in the table show that the users of the focal search engine consumed much less time on its app and visited the app far less frequently after service termination. The significant decrease in *duration* (column (1)) appeared to have been driven by the sharp decrease in *visit* (column (2)), because, even after the shock, no statistical difference in *duration per visit* was found between the participant groups (column (3)). The decrease in *share* (column (4)) corroborates the findings related to the reduction in *duration*. That is, the abolition of the PSTs structure significantly discouraged the users from engaging in search activities at the focal search platform, which led to penalizing the dominant search engine, as their users significantly reduced their visit frequencies and search durations. Interestingly, however, we found no significant variations in the users' search durations per visit, which mirrors the extent of search costs incurred by individuals. In the next section, we present an in-depth analysis of these findings, which was meant to shed light on the heterogeneous effects of PSTs on various social groups.

4.3. Heterogeneous Effects of PSTs Termination on Search App Usage

One of our primary objectives is to examine the effects of PSTs termination on the information inequality and digital divide between SEAs and SEDs. Correspondingly, we focused on how cessation affected users in diverse social groups who differed in search skills and search costs. That is, with all other factors equal, users with low search skills were assumed to bear relatively higher search costs than those with extensive proficiency in this task. For a comprehensive analysis, we considered a user's total search duration and their search duration per visit as measures reflecting search costs. Accordingly, we extended the specification in Equation (1), incorporating key socio-demographic characteristics (i.e., age, gender, education, and income) into a difference-in-difference-in-differences (DDD) model. For instance, the specification included an income moderator as follows (Equation (2)):

$$\begin{aligned} &FocalSearchAppDuration_{it} \\ &\quad = \alpha + \beta * Treat_i * After_t \\ &\quad + \gamma_1 * Treat_i * After_t * IncomeLowest_i \\ &\quad + \gamma_2 * Treat_i * After_t * IncomeLow_i \\ &\quad + \gamma_3 * Treat_i * After_t * IncomeMid_i \\ &\quad + u_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $IncomeLowest_i$, $IncomeLow_i$, $IncomeMid_i$ are binary variables that represent the user *i*'s monthly income and the high-income group

Table 3. Effects of PSTs termination on the usage of the focal search app

Variables	Total Usage Time	Total Visit Counts	Duration per Visit	Share (%)
Column	(1)	(2)	(3)	(4)
Treat × After	**-16.21*****	**-2.453****	-0.202	**-0.00619*****
	(4.249)	(1.184)	(0.124)	(0.00203)
Constant	85.65***	24.27***	1.934***	0.0429***
	(3.680)	(0.706)	(0.0840)	(0.00128)
Observations	17,856	17,856	17,856	17,856
Individuals	744	744	744	744
R-squared	0.007	0.004	0.001	0.004

Note. Robust standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. "Share" refers to the percentage of Focal Search App usage time out of the total mobile usage time (%). The unit of duration variables is minute. We controlled weekly and individual fixed effects for all models.

(*IncomeHigh*) is used as a reference. The groups were classified by income on the basis of the amount that users earned per month (i.e., *IncomeLowest*: less than 1 million KRW per month, *IncomeLow*: 1-3 million KRW per month, *IncomeMid*: 3-5 million KRW, *IncomeHigh*: over 5 million KRW). Likewise, we establish DDD models to capture the moderating effect on younger and older users compared with the users in their 40s (middle), low education level compared to high education level, and males compared to females. In the age analysis, we set the age of 40s as a reference to identify the discriminated effect between younger users and elderlies, and also, the proportion of people in their 40s was the largest in our sample. This age pattern accurately reflects the actual demographical characteristics of the Korean population and hence provides statistically stable outcomes.

Table 4 presents the results of the DDD analyses. Columns (1) to (4) show the heterogeneous effects of PSTs termination on the total usage time of the focal app (*duration*). The elderly in their 50s to 70s, people with the lowest income level, and those with low education necessitated additional search time. According to Goutam and Dwivedi (2012), time spent on search channels can be interpreted as search cost incurred. That is, the longer the search duration on the focal app, the higher the search costs incurred on the app. To examine the search costs more precisely, we analyze the heterogenous effects on *duration per visit*, and the results are located in columns (5) to (8). The elderly in their 60s to 70s spent more time on each visit to the focal app compared with the users in their 40s to 50s, and the lowest-income users spent more time on each visit to the app compared with their high-income counterparts. This implies that SEDs are more likely to suffer from an increase in usage time per visit (an increase in search costs) than SEAs. No significant difference was detected between males and females in both analyses (columns (4) and (8)).

Table 4. Discriminative effects of PSTs termination on the usage of the focal search app

Dependent Variables	Total Usage Time of Focal Search App				Duration per Visit of Focal Search App			
Reference Level	Age 40s	Income High-class	University-Graduated	Female	Age 40-50s	Income High-class	University-Graduated	Female
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × After	-28.29^{***}	-27.04^{***}	-20.00^{***}	-21.84^{***}	-0.280^{**}	-0.483^{*}	-0.0897	-0.191
	(8.804)	(7.150)	(5.598)	(6.533)	(0.125)	(0.252)	(0.130)	(0.157)
Treat × After × Age 20-30s	16.38				0.223			
	(14.30)				(0.199)			
Treat × After × Age 50-70s	**18.85^{*}**							
	(10.17)							
Treat × After × Age 60-70s					**0.434^{*}**			
					(0.258)			
Treat × After × Income Lowest-class		**71.17^{***}**				**1.689^{**}**		
		(20.07)				(0.755)		
Treat × After × Income Low-class		18.49				0.266		
		(12.28)				(0.344)		
Treat × After × Income Mid-class		12.87				0.443		
		(9.499)				(0.291)		
Treat × After × Highschool-graduated			**14.72^{*}**				-0.113	
			(8.595)				(0.218)	
Treat × After × Male				10.57				-0.0317
				(8.557)				(0.250)
Constant	85.59^{***}	85.65^{***}	87.05^{***}	85.65^{***}	1.931^{***}	1.934^{***}	1.977^{***}	1.934^{***}
	(3.668)	(3.667)	(3.756)	(3.677)	(0.0816)	(0.0838)	(0.0848)	(0.0840)
Observations	17,712	17,856	17,040	17,856	17,712	17,856	17,040	17,856
Individuals	738	744	710	744	738	744	710	744
R-squared	0.008	0.011	0.007	0.008	0.002	0.002	0.001	0.001

Note. Robust standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. We exclude teenagers from the age analyses in columns (1) and (4) since there were only a few individuals in our sample. We include only panels in their 30s and over in the education analysis in columns (3) and (7) to consider their final educational backgrounds (Refer to the classification scheme adopted by the US Consensus Bureau. https://www.census.gov/). We controlled weekly and individual fixed effects for all models.

5. Analysis of Other Mobile Behavior

Since the PSTs served as an information billboard, we expect that the termination of PSTs affects not only the information-seeking behavior within the focal search app but also the users' overall mobile behavior. To address how it affects users' mobile use, we analyzed 1) in what direction the abolition of PSTs affects the diversity of the entire app portfolio and 2) the usage of each category.

5.1. Diversity of Mobile App Usage

In this section, we focus on the perspective of mobile app usage diversity. Based on the frequency of visits by each category, we calculated the Gini coefficient for each user and each week. Here, the increase in the Gini coefficient means that the diversity of app use is reduced and the mobile behavior is more concentrated on specific categories, while the decrease in the Gini coefficient indicates that the users' mobile usage is more evenly distributed to each category. We conducted DID and DDD analysis on the Gini coefficient, and the method of analysis was the same as the specification in the previous section. Table 5 presents the results.

As a result of the analysis, the termination does not have an average effect on the entire treatment group (columns (1) and (2)). However, the results of the DDD analysis in columns (3) to (5) show that the Gini coefficient decreased differentially only in the people who are in their younger ages, with office jobs, and with higher income levels. That is, mobile behavior has become more diverse only in the SEAs since only the users with high digital literacy can actively use various apps from several categories to acquire information even after PSTs are eliminated, while the SEDs, who are considered to lack such ability, seem to show limited interest and utilize fewer sources of information which makes them hard to acquire proper amount and variation of information.

5.2. Spillover effect on Mobile App Usage

As addressed in section 4.2. and 4.3., the abolishment of PSTs brings a socioeconomic class-based discriminatory effect, with search underdogs remaining more in the focal search app, while their search costs are increasing and tech-savvy people leaving the focal search app. To identify how differentiated they are when considering their overall mobile behavior, even outside of the focal search app, we conducted another DID and DDD analysis regarding the spillover effect on other categories and the additive impact depends on demographic factors.

Table 5. Effects of PSTs on Gini coefficient for visit count for categories

Variables	Visit to Category	Visit to Sub-category	Visit to Category	Visit to Category	Visit to related Sub-category
Model	**DID**	**DID**	**DDD**	**DDD**	**DDD**
Reference Level			**Age 6070s**	**Job Not office**	**Income Lower-class**
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Treat × After	0.000449	-0.000159	0.00284	0.00229	0.00148
	(0.00135)	(0.000480)	(0.00209)	(0.00170)	(0.00168)
Treat × After × Age 2030s			**-0.00962****		
			(0.00487)		
Treat × After × Age 4050s			-0.000544		
			(0.00344)		
Treat × After × Office Job				**-0.00484***	
				(0.00278)	
Treat × After × Income Upper-class					**-0.00563***
					(0.00303)
Constant	0.752***	0.939***	0.750***	0.752***	0.876***
	(0.000780)	(0.000272)	(0.000912)	(0.000780)	(0.000911)
Observations	17,855	17,855	12,623	17,855	17,776
Individuals	744	744	526	744	744
R-squared	0.004	0.006	0.009	0.005	0.004

Note. Robust standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. We exclude teenagers from age analysis (third column) since there are only a few populations in our sample. We controlled weekly and individual fixed effects for all models.

Among the thirteen categories that were pre-classified in the given dataset, we only focus on the five major information-related categories such as finance, e-commerce, social media, internet service, and communication. The analysis method is the same as in the previous section, and the dependent variables are the *share* of each category, that is, the ratio of the total time spent on each category to the total mobile usage time. We decide *share* is the most suitable dependent variable since the purpose of the analyses is to indicate that the use of each category has changed among the entire mobile use. Note that the total duration and visit to overall mobile apps do not change after the abolishment of PSTs compared to the control group. Table 6 presents the results of the DID and DDD analyses.

First, what we pay attention to is the results of the DDD analyses in the even-numbered columns. In the e-commerce and social media categories alone, it is found that the use of young people in their 20s and 30s has increased discriminately. In other words, young people who are fluent in mobile use move to other channels to find the information they want, that is related to what other people are interested in real-time after PSTs is abolished, but older people who do not have such ability have difficulty getting information efficiently from other sources. In addition, referring to the results of the DID analyses in the odd-numbered columns, it is possible to interpret category spillovers with increased use in finance and communication and reduced use of e-commerce categories. It is very interesting that the abolishment of one service in a search engine even affects other categories, and the fact that it affects only some categories also suggests heterogeneous effects at the category level. To explain the changes in each category with one possible story, in the case of finance and communication categories, it can be interpreted that the use of the categories increases as they may serve as substitutes for PSTs in that each category provides real-time information and trendy information (issues) that others are acquiring. Conversely, e-commerce has decreased in use; if other categories have increased their use as channels for information acquisition, e-commerce is an outcome action consumed based on the acquired information, so it is interpreted that their use has decreased since the abolishment of PSTs, which has served as a billboard to attract consumers.

In conclusion, the analysis of changes in use by category outside the search engine also has two major implications as in the within-service analyses in the previous section: the effect of the abolishment of PSTs is differentiated by each socioeconomic class, and in particular, it acts in a more disadvantageous way for the weak with low mobile utilization ability. This gap between classes raises concerns about not only the gap in information acquisition itself but also the social disconnection between demographic groups, such as intergenerational conflicts by separating channels for information acquisition.

Table 6. Spillover effect on *Share* of other categories

Category	Finance		eCommerce		Social media		Internet Service		Communication	
Model	DID	DDD	DID	DDD	DID	DDD	DID	DDD	DID	DDD
Reference Level		Age 40s		Age 40s		Age 40s		Age 40s		Age 40s
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat × After	**0.00714***	0.0160**	**-0.00485****	-0.00714**	-0.00107	-0.00592	0.00430	-0.00300	**0.00711***	0.00492
	(0.00389)	(0.00704)	(0.00205)	(0.00351)	(0.00221)	(0.00551)	(0.00314)	(0.00917)	(0.00371)	(0.00655)
Treat × After × Age 20-30s		-0.0137		**0.00975***		**0.0196****		0.00483		-0.00962
		(0.0115)		(0.00564)		(0.00967)		(0.00947)		(0.0140)
Treat × After × Age 50-70s		-0.0126		0.00181		0.00450		0.0114		0.00473
		(0.00879)		(0.00456)		(0.00589)		(0.00968)		(0.00808)
Constant	0.0448***	0.0452***	0.0335***	0.0337***	0.0377***	0.0375***	0.0369***	0.0372***	0.142***	0.141***
	(0.00200)	(0.00201)	(0.00134)	(0.00135)	(0.00121)	(0.00121)	(0.00161)	(0.00162)	(0.00232)	(0.00232)
R-squared	0.017	0.018	0.005	0.005	0.004	0.006	0.005	0.006	0.021	0.024

Note. Robust standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. We exclude Naver from the Internet Service category. The dependent variable Share refers to the percentage of total usage time of a certain category in total mobile usage time (%). We exclude teenagers from age analysis since there are only a few populations in our sample. There are 17,856 observations with 744 individuals in all the DID analysis and 17,712 observations with 738 individuals in all the DDD analysis. We controlled weekly and individual fixed effects for all models.

6. Discussion and Implications

The digital divide mirrors existing inequalities in the socioeconomic situation, age, education, and income, among other aspects (Robinson et al. 2015). Citizens who are disadvantaged in the physical world (i.e., SEDs) are likely to suffer the same unfairness online because of their inferior digital skills (Hargittai 2002). With this consideration in mind, we inquired into how trend search structures may affect information inequalities between the "haves" and "have-nots," who vary substantially with respect to search skills. Our key findings suggested that the termination of these features negatively affects user groups with low search skills, such as elderly, low-income, and less educated individuals.

The DID and DDD approach empirical estimations collectively revealed further important insights into the effects of PSTs discontinuation on information inequalities between SEDs and SEAs. The termination may have widened the information inequality between the two groups owing to both *direct* and *indirect* causes. When all else was equal, the shutdown directly affected the SEDs by substantially increasing their search costs, as reflected in the sharp escalation of their search durations per visit (Goutam and Dwivedi 2012). This increase in search costs was far greater than that among the SEAs. To minimize the negative effects of PSTs termination, users can resort to alternative venues, such as apps in news and social media categories. However, differences in digital skills in general and mobile skills, in particular, prevent SEDs from actively sourcing important news updates and urgent information previously acquired from PSTs services at minimum search costs. The variations in the use of alternative sources indirectly exacerbated the imbalance in information availability between the "haves" and "have-nots." These findings led to the conclusion that PSTs abolition worsens information disparity, ultimately penalizing information-poor individuals.

Although research on the digital divide abounds with conceptualizations and empirical manifestations of this issue, little exploration has been directed to how such division can be influenced by search engines in general and popular searches in particular. Most studies converge around the adoption of and access to devices and network connections, paying scant attention to variations in users' search skills. However, our study lays a foundation for more research along this line of inquiry and highlights the reality that search technologies evolve at a pace that considerably surpasses users' skill levels.

Popular searches have been criticized for their unexpected side effects. For instance, these structures lend themselves readily to commercial advertising or exploitation by political interest groups for the purpose of rigging public opinion. These acts are easily achieved because search lists are determined not on the basis of the cumulative volume of search terms over time but on relative spikes in real-time traffic during a given period (i.e., the last hour). However, our findings showed that shutting down these functions penalizes users who are unskilled at searching (i.e., the elderly, the poor, low-income, and less educated individuals), thus widening information inequalities. Search term-based information search is an everyday ritual for billions of people around the world, but users differ dramatically in terms of search proficiencies. Given that information retrieval through the entry of search terms entails considerable cognitive load and knowledge, many low-skilled users may spend extra time on this task but end up finding irrelevant information. The use of the popular search terms lists "recommended" by the public, including search-adept users, may afford less privileged access to critical information (i.e., disaster updates) in real-time at minimum search costs. They can also help minimize the gap in the information available to unskilled and skillful users. Correspondingly, search engine companies and regulators who are in a position to either approve or deny such policies must work together to find optimal trade-offs in a manner that minimizes manipulation and maximizes protection for SEDs.

7. References

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