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Consumer information search behavior and purchasing decisions: Empirical evidence from Korea

Seung-Pyo Jun [a,*,1], Do-Hyung Park [b,*,1]

[a] Department of Industrial Information Analysis, Korea Institute of Science and Technology Information, 66, Hoegi-ro, Dongdaemun-gu, Seoul 130-741, Republic of Korea
[b] School of Management Information Systems, Kookmin University, 77, Jeongneung-ro, Seongbuk-gu, Seoul 136-702, Republic of Korea

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ABSTRACT

Recently, Internet activity by consumers adopting innovation or purchasing products has increased markedly. To understand this phenomenon, our study focuses on the correlation between purchase behavior and search activity. Utilizing the product classifications established in previous studies, we classify physical products into durable, nondurable, and industrial goods. We then empirically analyze case studies to determine the correlation between Internet searches and product purchases. Our research results show that the correlation between sales and search traffic is more significant for consumer goods than for industrial goods; furthermore, in the consumer goods category, search traffic is a particularly strong predictor of sales in the case of consumer durable goods. These results may be self-evident, implicit in the definition of each product category. However, the presented findings confirm that even among nondurable goods, search traffic can be a significant predictor of purchases, depending on both price and frequency of purchases. In contrast, for durable goods, search traffic may not be strongly indicative of actual purchases for new products, for which traffic simply reflects rising interest. We also show that PC searches are a stronger predictor of sales than mobile searches. The conclusions drawn from this study provide an important foundation for effectively using search statistics in technology business management to formulate marketing strategies as well as to forecast and analyze the adoption of new technology based on real-time monitoring of the changing involvement with each product.

1. Introduction

Recently, many researchers have analyzed so-called big data in order to empirically verify the correlation between series of behaviors exhibited by consumers and their subsequent purchases. In particular, researchers have focused on performing various types of analyses on the basis of consumers' Internet search activity, as reflected in data such as search traffic. Although this approach has yielded many useful empirical findings, various methodological challenges nonetheless hamper it. For example, critics maintain that some researchers have failed to adequately understand and classify the objects of these searches.

We add to the literature by investigating whether the relationship between search behavior and purchases depends on the product type. We comparatively analyze the relationship between search and purchase behaviors by differentiating between product types, using case studies of products identified as representative of each product category. In this study, we use data provided by Statistics Korea (KOSTAT) and leading search engine websites in Korea, which allow us to perform a more rigorous empirical analysis of differences previously assumed only to exist when consumer search activities are distinguished by product type.

Based on whether a product is tangible or intangible, products can first be divided into goods and services (McDermott et al., 2001; Walsh and Linton, 2011).[2] Goods (physical products) are then further divisible into durable and nondurable goods, according to their duration and form of use. Durable goods generally refer to tangible products that can be used multiple times, such as refrigerators, and machines, whereas nondurable goods refer to tangible products that are generally expended after two or three times of use, such as food and cleaning products. Services are intangible products that are inseparable and are generally highly variable and perishable. Products can also be classified

* Corresponding authors.
E-mail addresses: spjun@kisti.re.kr (S.-P. Jun), dohyungpark@kookmin.ac.kr (D.-H. Park).

[1] These authors have equally contributed to this work, so you can contact anyone about the work.

[2] Alternatively, in innovation studies, tangible products are sometimes referred to as physical products in contrast with services, and the differences are explained in terms of innovation.

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on the basis of the purpose of use into consumer goods and industrial goods (Kotler et al., 2014; Kotler and Keller, 2007).[3]

In this study, we first classify products into consumer and industrial goods on the basis of their intended use. Then, we classify consumer goods into durable and nondurable goods on the basis of their durability and utility. Next, we select a representative product for each of these categories and comparatively analyze the relationship between search activity and purchasing behavior in Korea. In addition, we account for the rising interest in or the effects of concentrated marketing efforts that occur when a new product is launched. In the case of consumer durables, which exhibit a strong correlation between searches and purchases, we further examine the possible effects of a "hype cycle" that may exist when a new product is launched.

Our study is of use to those that wish to utilize consumer search-activity data since our conclusions offer a framework for directing various activities in technology management, and marketing. A company's efficacy in market information processing—involving the gathering, sharing, and use of consumer information related to the market—plays an important role in determining the success or failure of its products (Ottum and Moore, 1997). In general, companies implement marketing strategies with the aim of transforming a low-involvement product into a high-involvement product (Kotler et al., 2014). This study thereby offers a method for monitoring the involvement of individual products in real time and tracking how products shift from being low-involvement to high-involvement products. The conclusions drawn from this study would have practical value if they are selectively applied to developing effective marketing methods.

The remainder of the paper is organized as follows. Chapter 2 introduces the theoretical background of our research by briefly explaining how products are classified. We also outline the respective theories pertaining to purchase behavior and information searches and review previous studies in this field. Chapter 3 explains our research model, the cases we examine, and the methods used to collect data. Chapter 4 presents our research results, and Chapter 5 addresses issues related to this study that require further discussion, including mobile search traffic and forecasting using the vector error correlation model (VECM).

2. Theoretical background and hypotheses

2.1. Product type depending on product characteristics

Marketing managers typically classify products (consumer and industrial goods) according to a range of criteria, such as durability, tangibility, and purpose, in order to establish an optimal marketing mix strategy (Murphy and Enis, 1986). At the broadest level, products can be divided into consumer and industrial goods according to their intended use. The term "consumer goods" refers to products purchased by general consumers for their own specific purposes, whereas the term "industrial goods" refers to intermediate goods such as raw materials and parts that are input into the manufacturing process to make final products. Industrial goods can be further classified according to the manner of their input and relative cost into subcategories, such as materials and parts, capital goods, supplies, and services.

Consumer goods can also be classified into durable and nondurable goods. Durable goods refer to physical (tangible) goods expended over the long term as the convenience obtainable from their use gradually decreases; in contrast, nondurable goods refer to goods consumed after short-term use. This classification applies to consumer goods: sewing machines and electric refrigerators for home or family use belong to the former category, while groceries, soap, and cigarettes are examples of the latter. The boundaries of the classification are somewhat fluid; for example, clothing and books may be kept and used by some consumers for several years, but they are usually classified as nondurable goods. Durable goods usually involve a large amount of human resources for sales and service. Their price is set to include a high margin of profit, and a strong warranty may be offered to appeal to the buyer. In comparison, nondurable goods, such as beer or soap, are purchased more frequently; therefore, these types of goods ought to be made widely available for purchase, priced with a smaller profit margin, and marketed through large-scale advertising campaigns to induce use, with communication aimed to increase consumer preference.

Lastly, goods can be classified as tangible (goods) or nontangible (services); the term "services" refers to the act of providing convenience to people as a commodity. Services do not result in ownership over things and they cannot be transacted in separation from their production, since the production of a service is realized only at the moment its benefits are delivered to a consumer. Services consist in heterogeneous outputs produced upon order, typically realized as the activities of the producer in response to consumer demand. In summary, services are intangible, inseparable, and have a high level of variability and perishability, and thus they require a high level of quality control and demand reliability as well as adaptability on the part of the supplier (Kotler et al., 2014; Sousa and Wallace, 2006). Furthermore, as observed in innovation studies, the process of innovating and adopting services can unfold in a manner very different from the innovation of physical products. For example, while the innovation of physical products proceeds sequentially from product innovation to process innovation (Abernathy and Clark, 1985) in the service sector, this sequence may be reversed (Barras, 1986). We thus limit the focus of this study to physical products (goods).[4] This study aims to verify how well web search traffic data can predict product sales based on distinctions among product types (i.e., durable and nondurable consumer goods).

2.2. Web search traffic information

Can the keywords people use in Internet searches forecast their economic activities? This depends upon what we mean by "forecast." Google Trends recently released real-time statistics on search keywords and many researchers have conducted studies based on these data. The advantage of using search traffic tools, such as Google Trends, is that it makes it possible to analyze trends close to real time: the advantages of using such data have been demonstrated mainly in applications, making near-future, rather than long-term, forecasts.

Researchers have used various indices to measure product sales and innovation adoption. Watts and Porter argued that the technology lifecycle can be measured based on the science citation index, newspaper abstracts, and patents (Watts and Porter, 1997), and there are many ongoing attempts to analyze new and emerging technology based on various information such as research publications and patents (Robinson et al., 2013). By comparison, forecasting or analysis utilizing web search data has become prominent only relatively more recently.

Ginsberg et al. (2009) presented the results of their analysis performed on data obtained from an early version of the Google Flu Trends search engine, used to forecast the current flu level. They presented a computer model able to convert the unprocessed search data into a real-time monitoring system capable of accurately forecasting flu virus activity one to two weeks in advance of the forecasts issued in conventional reports by the Centers for Disease Control and Prevention in the United States. This study earned broad recognition for the wide-ranging potential of using search traffic to make forecasts.

[3] In addition, products have also been classified as high-involvement or low-involvement based on the varying levels of importance or interest perceived by individual consumers who are affected by marketing stimuli. We chose not to adopt a classification based on the level of involvement in our comparative analysis since we analyze search traffic for individual products, in which case the involvement is self-evident by definition.

[4] In the case of services, the name of a service may encompass a broad range of content (e.g., consulting, restaurants, and financial services) and consumers may perform searches for a wide variety of purposes; therefore, it is difficult to consider these searches as representative. Moreover, it is difficult to determine any direct causality between search intent and the purchase. For these reasons, we exclude the category of services from our analysis.