Technological Forecasting & Social Change 81 (2014) 82–95

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

A study of the method using search traffic to analyze new technology adoption

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ARTICLE INFO

Article history:
Received 14 June 2012
Received in revised form 4 February 2013
Accepted 7 February 2013
Available online 13 March 2013

Keywords:
New technology adoption
Search traffic
Google trends
Brand search
ARIMA
Time series decomposition method

ABSTRACT

Various types of indices have been developed and applied for the purpose of identifying emergent technologies and forecasting their adoption. Recently, researchers have proposed search traffic analysis as a new method for tracking changes among consumers and utilizing this information to conduct further market research. Now with the onset of big data era, various attempts are being made to analyze the immense body of information made available by hidden traces left behind by consumers. In the same vein, our present study seeks to draw attention to the analytical advantages of utilizing search traffic. In this study, we use search traffic to analyze the adoption process of a new technology, in this case the technology of hybrid cars, for the purpose of verifying the potential value of conducting adoption analysis based on search traffic and we also propose a more refined method of analysis. First, we undertook to examine the keyword unit used in the searches, in order to refine our analysis of search traffic and thereby obtain greater practical utility. This was accomplished by comparing technology searches that specified the technology name with searches that specified the brand name. For each respective case, we also performed comparative analyses examining instances in which consumers simultaneously included the representative attributes of a product in their search.

Our research found that the traffic of searches that specify a product's brand name was significant for explaining sales. Therefore, in the conclusion of this paper we argue that if the unit of search is properly refined, search traffic can indeed serve as an extremely useful method for analyzing or forecasting sales volume. Notably, brand-focused search traffic exhibited a superior ability to forecast sales volume compared to macro-indicators such as GDP growth or WTI prices that had been used to forecast car demand in preceding studies. Forecasting based on search traffic was even superior to forecasts using other bibliometric indices such as patent applications or news coverage.

1. Introduction

Market competition among companies, accelerated launchings of new products, and the competition for technological development have all resulted in shortening the life span of technologies. For these reasons, it has become increasingly important to analyze the adoption of technologies and products as part of the effort to forecast technologies and demand. One leading method used for conducting such analyses of technology adoption, particularly those focusing on new technologies, is the technology life cycle method. The life cycle method is a macroscopic approach that is frequently used in bibliometrics or business administration studies. However, this life cycle approach can be problematic because it is narrowly focused on the producers' perspective. This limits our ability to use the life cycle to forecast the current market, since this market is now often characterized by the leadership of consumers [1].

To overcome the limitations of such analyses based on the producers' perspective and to enhance the accuracy and explanatory power of technology and demand forecasting,

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http://dx.doi.org/10.1016/j.techfore.2013.02.007

researchers have also deployed various approaches from a microscopic perspective. Some representative examples of such approaches include marketing research, which targets consumers, or the business survey index, which targets producers. Such research is dependent on the use of a survey-based method, a method that requires a large amount of financial cost and time investment. These approaches are also hampered by the inherent limitations of such sample-based research and by psychological complications such as cognitive dissonance.

This study adopts a macroscopic approach that overcomes the limitations of such microscopic, survey-based approaches, while also moving beyond the conventional focus on producers, instead analyzing the market from the consumers' perspective. For this purpose, our study focuses on search traffic, which we argue to be a new index that will better equip us to analyze the adoption of new technologies. Search traffic gives a direct indication of consumers' behavior while also providing macroscopic information close to the total population. Above all, search traffic is a method worthy of our attention because it is economically advantageous in terms of expense and time and it enables us to analyze hidden consumer intentions [2].

With the arrival of the big data era, various attempts are being made to analyze the wealth of data that is unconsciously left behind by consumers, and this study explores a method of utilizing search traffic to understand the adoption of new technologies. Our study examines search units in order to secure a more practical method of applying the search traffic data. In this study, we regard new technology as an embedded product.

2. Theoretical context and preceding research

2.1. Theoretical context

Marketing theory defines adoption as the decision of an individual to become a regular user of a certain product [1]. In innovation theory, adoption is regarded as the most advanced step of the process, since it represents the decision to utilize the innovation without any reservation [3]. Our present study shares this concept in as far as we regard adoption as essentially the final step of selection, consisting of the sale of a product applying new technology, but our conceptual framework is also broader in scope, since we regard the adoption process as the entirety of the process encompassing awareness, interest, evaluation, use and adoption. The major theoretical backgrounds to this study are briefly outlined in the following.

2.1.1. Consumer behavior model

The study of consumer behavior refers to the study of the methods used by individuals, groups and organizations to select, purchase, use and process products, services, ideas or experiences for the purpose of satisfying their primary and secondary needs. Such consumer behavior is impacted by cultural, social and personal factors, and numerous types of consumer behavior models have been proposed to better understand such consumer behavior. According to the stimulus–response model of buyer behavior, first, marketing stimuli and environmental stimuli enter the consciousness of the consumer. The psychological process combines with special consumer characteristics to influence the decision making process and ultimately induce the decision to purchase. In other words, the consumer behavior model addresses the process that occurs within the consumer's consciousness in between the input of the external marketing stimuli and the final buying decision.

When the purchase decision making process is examined based on this consumer behavior model, it can be broadly distinguished into five stages, consisting of 1) problem awareness, 2) information search, 3) evaluation of alternatives, 4) decision to purchase, and 5) actions following purchase. This model emphasizes that the process leading to the purchase is initiated long before the actual act of purchase, and that its results linger long after the purchase. However, consumers do not undergo all five stages in all cases when they purchase a product. In other words, some consumers sometimes simply skip over a certain stage, and some even move through some of the stages in inverse sequence. As in the consumer behavior model, the differences in cultural, social and personal factors inevitably result in diversifying the forms of adoption exhibited by consumers in their consumption of new products in particular [1].

In regards to search traffic, which is the object of this study, the dynamic nature of information searches must be emphasized. Consumers collect information to learn about competing brands and their characteristics. The first stage presented in Fig. 1 indicates the total set of brands available for use by the consumer. In this stage, consumers have knowledge of only a few of the brands, and these known brands constitute the “awareness set.” Even among the brands within the awareness set, only several of them fulfill the criteria that will determine the consumer's initial purchase, and these brands constitute the “consideration set.” Consumers collect further information regarding these brands and winnow out a few brands that are strong candidates for selection, and these then constitute the “choice set.” All brands within the choice set are acceptable, and the consumer selects the optimal choice from within this choice set [1].

2.1.2. Consumer adoption model

In technology innovation theory, the consumer adoption model is the key theoretical component for explaining consumer behavior. In this context, innovation pertains to goods, services or ideas that people perceive as new, regardless of how long they have existed. The above definition of innovation is based on the work of Rogers [3], who defined the innovation diffusion process as the “the dissemination of a new idea generated by invention or creation among the final users or adopters.” In other words, the consumer adoption process scrutinizes the mental experiences that the individual undergoes from the moment he or she first hears of the innovation up to the stage of final adoption. The adopters of new products proceed through five stages in the adoption process, namely the stages of Awareness, Interest, Evaluation, Trial and Adoption [1]. The approach to the adoption process outlined by Rogers highlights the mental process experienced by the individual. It is therefore qualifies as an approach from the point of view of the user (or consumer), in contrast to the life cycle, which is a conventional approach that focuses on the producers. Among the five stages listed above, the Interest stage is the one most deeply related to search traffic, which is the subject of our attention in this study.

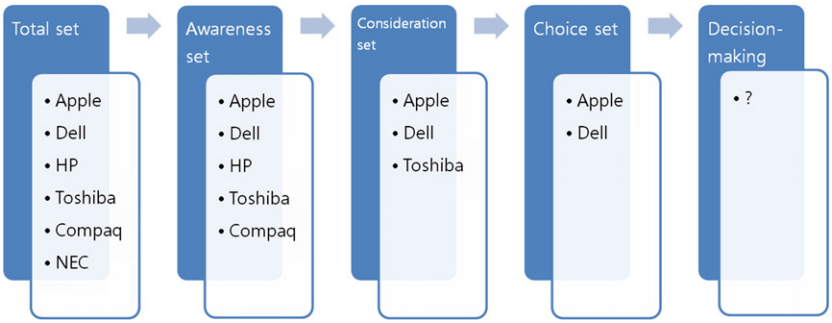

Fig. 1. Sets within the consumer's decision making process involving dynamic information searches. Source: [1], (modified).

Rogers [3], in the course of explaining the differences in the preparation taken for the usage of new products and the impact of individual factors, defined the innovativeness of an individual as the relative speed of a particular individual in adopting new ideas compared to other members within the social system. In each product field, there are innovators, early adopters, etc.

2.2. Preceding empirical studies and distinguishing features of the current study

2.2.1. Preceding studies related to adoption forecasting

Hybrid cars, which are the object of the case study in this present research, belong to the automobile industry and therefore they are inevitably impacted by that industry's life cycle. Therefore, it is necessary to examine the environmental factors that impact automobile demand. Generally, the relevant factors include GDP growth rates, unemployment rates, and the consumer confidence index. Population, WTI prices, automobile prices, and housing prices, etc. are sometimes also taken into consideration as influences on demand [4].

There are thus multiple types of factors that impact car demand, such as income level, population, the number of households, car prices and maintenance costs, road conditions, and institutional factors. Among these, however, the factor that is regarded as having the closest correlation is GDP growth, which is a proxy variable signifying the level of income [4–7].

While GDP growth is identified by business administration studies as one of the leading environmental variables correlated to automobile demand, WTI price is the key environmental factor when analyzing demand for hybrid cars. The global trend toward embracing green products is reinforcing consumer awareness regarding environmentally friendly consumption practices, and fluctuating WTI prices impact not only a country's overall economy but also the energy consumption practices of individual consumers, which we must not neglect to consider. The reason that the WTI price, which has such an intense correlation to the sales of hybrid cars, remained largely unmentioned as a correlative factor in car sales is because the changes in WTI price influence preferences in car model selections rather than car sales overall [4].

The methods of approach compiled in Watts and Porter [8] show us the results of research on technology adoption based on bibliometric approaches. As shown in Table 1, Watts and Porter identified and organized the key bibliometric indices that enable us to approach from the early research and development stage to the adoption stage.

Meanwhile, Martino [9] argued that it is possible to derive the technology life cycle by utilizing the five indices employed in bibliometrics as presented in Table 1. Martino's study observed that an initial increase of hits for indices related to basic research is followed by an increase in indices related to applied research as applied research increases. Meanwhile, there is a corresponding decrease in the hits for basic research indices, and we can deduce from this that as changes occur in the technology life cycle, the hits for indices of the subsequent stage will increase. Although an attempt was made to generalize from these results, Järvenpää [10,11] argued that the categorization of stages shown in Table 1 fails to express the representative features of each stage. Though each individual index may indeed fail to directly indicate the technology life cycle, however, components such as patents, paper publications and news mentioned in Table 1 are actively used for forecasting the adoption of new technologies.

As examined above, the GDP growth rate and the WTI price have been presented as significant variables by preceding researchers in the field of business administration to forecast car related demand, and patents and news have been utilized actively by researchers in bibliometrics. In accordance with the precedents set by such macroscopic research, we selected the variables to be used along with search traffic for our comparative analysis, as presented in Table 2.

2.2.2. Preceding studies utilizing search traffic

The paper published by Ginsberg et al. [14] in *Nature* presents a model for forecasting the current level of influenza based on an analysis of data acquired from past queries made

Table 1
Technology life cycle indices.
Source: [8].

Factor	Indicator
R&D Profile	
Basic research	Items in e.g. Science Citation Index
Applied research	Items in e.g. Engineering Index
Development	Items in e.g. U.S. Patents
Application	Items in e.g. Newspapers Abstracts Daily
societal impacts	Issues in Business/Popular Press abstracts
Growth rate	Trends over time in number of items

Table 2
Macroscopic variables for measuring technology adoption (in the case study of automobiles).

Perspectives	Measurement	Realated articles
Business administration	GDP growth	CAR research [4,5], Sivak and Tsimhoni [6], Haugh et al. [7]
	WTI price	Car research [4]
Bibliometrics	Patents	Watts and Porter [8], Chen et al. [12]
	News	Lind [13], Järvenpää [10,11]

in Google's search engine. This paper presented a computer model that was able to convert the unprocessed search data into accurate forecasts of the activity of the influenza virus, available 1 to 2 weeks in advance of the conventional report publicized by the Centers for Disease Prevention and Control (CDC). This work precipitated awareness of the diverse potentials of forecasting using search traffic.

The research by Choi and Varian [15] was a precedent that provides a strong illustration of the possibilities of demand forecasting enabled by search traffic, the method that our present study seeks to demonstrate. Choi and Varian found that Google Trend was able to enhance forecasting of current economic activity over time. Their explanation of economic activities covered categories such as car sales, house sales, retail and travel, etc. The authors claimed that there were cases when it was useful to forecast conditions in the present rather than in the distant future, since this assists in identifying the "turning point" in economic time. For example, if there has been an increase in searches for "real estate agencies" in a particular location, this can indicate a rise in housing sales in this location within the near future. Since this paper's analysis focused on corporate brands, however, its objective differed from that of our present study, which seeks to observe consumer behavior pertaining to new technologies.

As demonstrated in the research by Choi and Varian [15], search traffic can be employed for forecasting demand, but it can also be utilized in entirely different fields such as election forecasting in politics or in the social sciences. The study by Lui et al. [16] offers an example of such other potential uses for search traffic. Their research examined the possibility of forecasting the success of candidates for the U.S. congressional elections in 2008 and 2010 using the search traffic provided by Google Trends and the authors concluded with the argument that search traffic is not yet a significant method for forecasting election outcomes.

Recently, the research by Vosen and Schmidt [17] compared the University of Michigan Consumer Sentiment Index (MCSI) and the Consumer Confidence Index, indices used to identify consumption trends in the United States, with the search traffic results provided by Google Trends and concluded that the search traffic made available by Google can exhibit superior forecasting ability compared to formerly used survey-based indices. This study empirically demonstrated that search traffic can offer forecasts of individual consumption that rival forecasts made available through microscopic analysis. Jun [18] conducted comparative analyses of macroeconomic indicator variables such as oil prices and GDP growth rates to demonstrate that consumers' hype cycles can be observed through search traffic. Jun [19] also compared hype cycles among actors within the socio-technical system using search traffic.

Such preceding studies on search traffic show that search traffic can serve as a proxy measurement of social phenomena and can yield analytical results that are comparable to conventional surveys in providing macroscopic forecasts such as forecasts of demand and changes in consumption, but they also provide the caveat that search traffic can reflect both positive and negative interest and therefore has limitations when applied to certain fields. Also, its use is currently limited by the nearly complete absence of analyses examining its correlation to environmental variables and comparisons to conventional forecasting indices.

3. Research methodology and case study

3.1. Research model

Our present study seeks to illuminate whether the traffic data on searches made in specific units can be productively used to forecast the adoption of a new technology as reflected in sales volume. First, we conducted a comparative study examining not only the impact of search traffic for new technologies (or product groups applying new technologies) on the forecast of hybrid car sales but also the impact of search traffic for Prius, the representative product brand, on the forecast of hybrid car sales. In the hybrid car market, the total sales of the Prius occupies nearly half of the total sales of hybrid cars, and the Prius brand enjoys such absolute dominance in the hybrid car market that consumers generally associate the very idea of hybrid cars with the name Prius.

Since Choi and Varian [15] have already examined the sales forecasting ability of corporate brands, we used the brand names of products for the present comparative study. Another attribute is the price, which is an important element in searches conducted by consumers. According to the preceding study by Su [20], searches for both prices and non-price product information constitute an important percentage of all searches. This can be regarded as an indication that search traffic reflects a variety of intentions, reflecting the intent of finding not only price information but also other attributes of the products. Therefore, a comparative study was conducted to identify the correlation between sales and the search traffic in which consumers simultaneously sought the price while also seeking information on hybrid cars or the Prius.

Lastly, we conducted a comparative study of cases where consumers searched simultaneously for information on mpg, which is one of the competitive attributes of hybrid cars included among the various types of non-price product information examined in the research by Su [20]. As regards information searching behavior on the web, information on factors such as product brand, price and mpg are likely to be sought in search activities by consumers who have already previously acquired relevant knowledge or who are conducting a repeated search, rather than by those who are conducting an initial search. For this reason, we can presume that such information reflects search activities of those who have psychologically approached closer to a purchasing decision.

The research model presented in Fig. 2 compares the explanatory significance of relevant conventional indices and search traffic regarding the decision to purchase, which is the

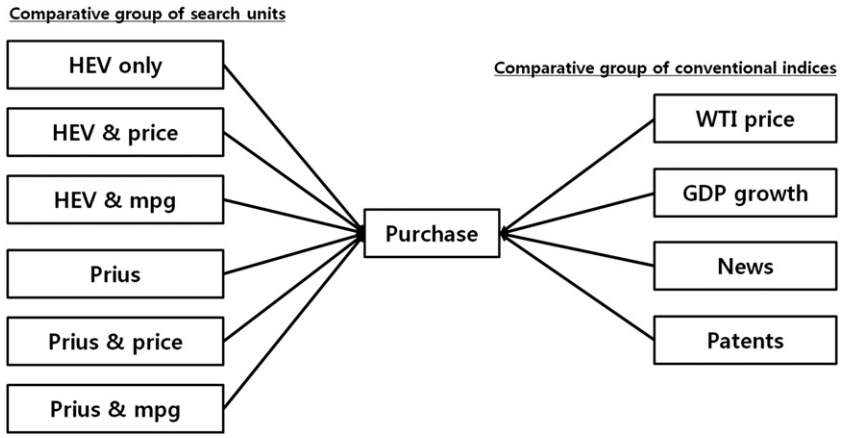

Fig. 2. Research model for a comparative study of explanatory factors for the purpose of forecasting purchases.

final stage in the process of adopting new technology. In this model, each variable is capable of explaining purchasing activity, with one to one correspondence. As explained above, when studying search traffic, we compared cases in which searches were conducted using respectively the name of the new technology, the brand name, the price, and the mpg.

3.2. Research hypotheses

Our hypotheses regarding the unit of search used in search traffic, as explained above in Fig. 2, were established for the purpose of comparing the traffic of searches targeting the name of the technology, the brand name, the price, and the mpg. In accordance with the five-stage purchasing decision model provided by the consumer behavior model, these research hypotheses are null hypotheses used to test whether an increase in activity for a specific type of search corresponds with an increase in purchasing activity for the product applying the technology in question.

H_0 A1. There is no positive correlation between the activity of searching for hybrid cars and the activity of purchasing hybrid cars.

H_0 A1-1. There is no positive correlation between the activity of searching for Prius cars and the activity of purchasing hybrid cars.

H_0 A2. There is no positive correlation between the activity of simultaneously searching for hybrid cars and their prices and the activity of purchasing hybrid cars.

H_0 A2-1. There is no positive correlation between the activity of simultaneously searching for Prius cars and their prices and the activity of purchasing hybrid cars.

H_0 A3. There is no positive correlation between the activity of simultaneously searching for hybrid cars and mpg data and the activity of purchasing hybrid cars.

H_0 A3-1. There is no positive correlation between the activity of simultaneously searching for Prius cars and mpg data and the activity of purchasing hybrid cars.

The following are the research hypotheses addressing the indices shown in Table 2 for the purpose of comparing the search traffic results for specific search units.

H_0 B1. There is no positive correlation between the news coverage regarding hybrid cars and hybrid car purchasing activities.

H_0 C1. There is no positive correlation between patent applications related to hybrid cars and hybrid car purchasing activities.

H_0 D1. There is no positive correlation between the WTI price and hybrid car purchasing activities.

H_0 E1. There is no positive correlation between the GDP growth rate and hybrid car purchasing activities.

If a particular null hypothesis pertaining to search traffic is rejected and the significance is high in relation to conventional indices such as the WTI price, the GDP growth rate, patent applications and news coverage, this would verify the utility of search traffic for the purpose of forecasting demand in the context of analyzing new technology adoption. Furthermore, the results would provide important insights into the implications of the unit used in searches when we seek to utilize search traffic data. The hypotheses were all established in terms of individual relation to purchasing activities, and were analyzed based on one to one correspondence in correlation to purchasing activities (univariate regression).

3.3. Case study: hybrid cars

We must consider several issues when selecting a case study for the purpose of examining the correlation between the web search activities regarding new technologies and their sales. First, we require a case involving a technological innovation that is similar in degree to the paradigm change identified in explanations of the technology life cycle. In the technology life cycle, the level of the technology involved is of such a degree that it accomplishes innovations or parts or materials or innovations in processes commonly applied to products sold in differing markets. This represents a broader

concept of technology, in which a change occurs in the dominant design to cause technological enforcement. Therefore, we require a case involving the emergence of a new technological innovation at a level that precipitates changes in the core technological paradigm or technological standard that had previously led a specific industry. Another consideration was that we required a relatively long-term technological life cycle that transcends noise from the external environment, with preference for cases which have recently passed or approached the growth phase. This is because it was only relatively recently that we have been able to accumulate information on search traffic and that we have begun to recognize the importance of information searches on the web.

To meet these stipulations, hybrid cars offer an ideal case study. The hybrid car industry has recently completed its introductory phase and is now approaching its growth phase, and since these new hybrid vehicles replace conventional internal combustion engines, they can be regarded as representing a change in the technological standard posing a challenge to the existing car industry's paradigm. In particular, hybrid cars have made environmental friendliness and mpg emerge as crucial attributes in the automotive market. In consideration of these aspects, we selected the hybrid car market as the case study for this research.

3.4. Collection of data for analysis

Since we adopted webometrics as a research method that would replace the conventional survey method, it was critical above all to use data that had been objectively collected and analyzed. For this reason, in this study we used only information provided by highly credible governmental or public institutions or information made available by dominant corporations, as indicated in Table 3. Also, to ensure objectivity in information collection and to enable automated or systematic collection and utilization in the future, all of our data relied on public information accessible via the web.

The advantage of utilizing Google trends is its process of normalization. Research case studies in the past used absolute values (for example, the number of hits, etc.) and hence failed to exclude environmental factors behind consumer exposure resulting from the overall increase in news volume or the number of web pages. By contrast, all of the results of the search statistics in the Google trends data undergo a normalization process, dividing them by a common variable to eliminate the influence of external forces. Through this method, it becomes possible to compare the basic features of each set of data. The frequency of all other bibliometric indices, such as news and patents, are also measured in relation to the total data for the time period in question, and is again divided by the total average to ensure that normalized intensities are used in all comparisons. The market sales volume is also divided by the total sales volume to yield the sales market share of new products submitted to analysis.

3.5. Analysis of source data and the conversion of time series data

To examine outliers, this study analyzed the Stem-and-Leaf plot of the six types of variables explained above. As a result, outliers were found in the search traffic, the WTI price and the GDP growth rate. The WTI price exhibited abnormal increases at two points in time, namely in the second and third quarters of 2008, while search traffic exhibited an abnormal increase only once, in the second quarter of 2008. This can be explained as a phenomenon caused by the outlier increase in the WTI price. Outliers for the GDP growth rate were observed at three points in time, and an abnormal decrease was observed over the course of three quarters, from the third quarter of 2008 to the first quarter of 2009. The outliers mentioned above all resulted from actual economic changes rather than from errors in measurement and we did not implement any separate exclusion measures because the number of targets observed for analysis was insufficient and the following time series data conversion may reduce impact. The same method was used to examine outliers for variables pertaining to search units, and we discovered outliers among the majority of these variables. In particular, searches including mpg exhibited multiple outliers, but as above, we took no exclusionary measures for these outliers.

The conventional method of analyzing time series data is the time series decomposition method, which decomposes and analyzes each factor that influences changes in the time series data. Factors that influence changes in the time series data include 1) the trend component, 2) the seasonal component, 3) the cycle component and 4) the irregular (remainder) component. This study also decomposed four components and selected the trend component and the cycle component, which are important for long-term forecasting, to conduct an analysis of correlations among the time series data. The seasonal component was eliminated partly for the purpose of comparing long-term trends, but also because only some of the major variables exhibit a seasonal component and therefore the seasonal component could create noise when examining the significance among these variables. The trend-cycle estimation performed after excluding the seasonal adjustment component and the irregular component (errors) was used to convert the time series data of all the variables. Figs. 3 and 4 present comparisons of the actual values and the conversion values for

Table 3
Data sources for each major variable and index.

Variables and indices	Site	Explanation
Search traffic	Google trends	Weekly and quarterly search traffic in the United Sates (2004–Present)
Patents	USPTO	Quarterly patent disclosures in the United States (2002–Present)
News	Google news archive	Monthly and quarterly English-language news (2002–Present)
Oil prices(WTI)	U.S. Energy Information Administration, EIA	Monthly WTI crude oil price (2004–Present)
GDP growth rate	U.S. Department of Commerce	Quarterly U.S. GDP growth rate (2004–Present)
Market share	Hybridcar.com	Monthly, quarterly market share rate of case study technologies among new cars in the U.S. (2004–Present)

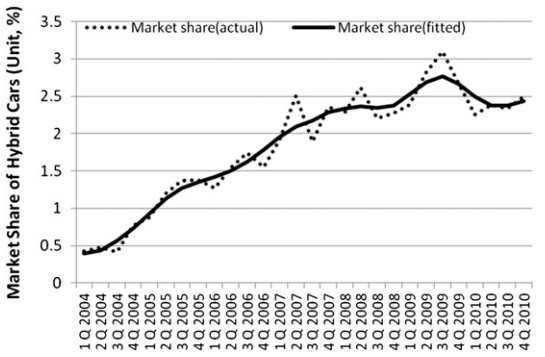

Fig. 3. Comparison of the actual hybrid car sales rate and the trend cycle model.
Source: Hybridcars.com, 2011. 6. (last accessed).

the sales rate and the search traffic, which were our key variables.

Once converted into the trend cycle model in this manner, the time series data also reduces the outliers that were present in the raw data. Among the three variables that exhibited outliers in the source data – namely the search traffic, the WTI price and the GDP growth rate – the search traffic and the WTI price no longer exhibited outliers after conversion into the trend cycle model. Notably, however, only the GDP growth rate continued to exhibit outliers in the identical three points in time. Of course, no new outliers were observed in the other three types of variables (patent applications, news coverage and sales). Meanwhile, outliers were also reduced and were hardly observable in the search traffic variables for specific search units with the exception of the traffic of searches including mpg, which was the only case which continued to include the presence of three or more outliers. The time period in which the outlier was present was lagged one quarter behind the GDP growth rate.

4. Results

4.1. The results of observing correlations between the sales rate and the variables used in preceding studies

Fig. 5 explores the correlation that can be found between the traffic for searches specifying the name of a technology

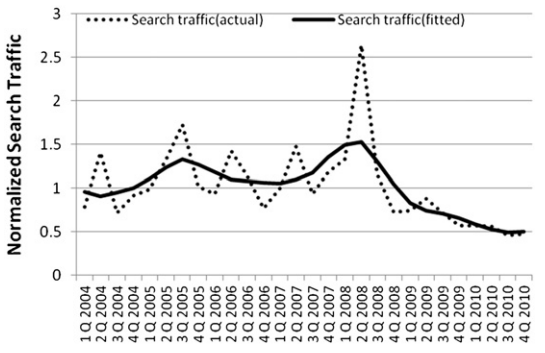

Fig. 4. Comparison of the actual measured value of search traffic intensity and the trend cycle model.
Source: Google trends, 2011. 6. (last accessed).

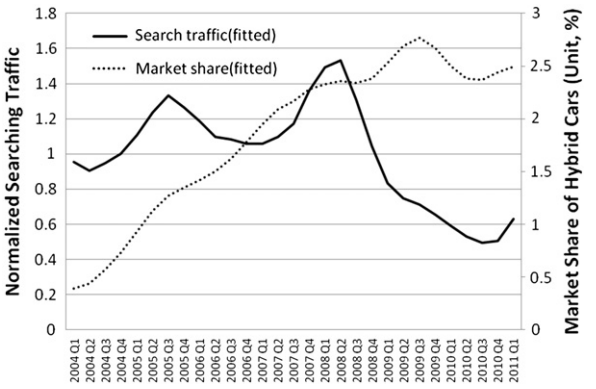

Fig. 5. Comparison of the search traffic and the market share for hybrid cars in the U.S.
Source: Google trends & Hybridcars.com, 2011. 6. (modified).

(hereinafter referred to as "technology search") and the sales. Fig. 5 shows a pattern whereby the search traffic diverges greatly from the sales rate during the period in 2007–2008 when the market share of hybrid cars in the U.S. exceeded 1.5–2.0%. While on the one hand, the sales rate exhibited a nearly linear trend of increase, on the other hand, the search traffic followed a markedly different trend.

By contrast, according to Fig. 6, WTI prices and the sales rate for hybrid cars exhibited a relatively similar trend over the course of the entire period, supporting the likelihood that the WTI had a large impact on the expansion of the hybrid car market, corroborating the results of preceding studies presented in Table 2. Though there were some segments in which the purchase rate of hybrid cars continued to rise even during the period when the WTI was in decline, overall the trend was verified to be similar. The data in Fig. 6 demonstrates that in contrast to the similarity of the WTI trend, the GDP growth rate did not exhibit any significant correlation to changes in sales. The outcomes of various preceding studies shown in Table 2 had already established that the GDP growth rate was a significant environmental variable in the car market, and the fact that the GDP growth rate did not exercise any particular impact in this case may be attributable to the unique product characteristics of hybrid cars, or may be explained by the abnormal conditions imposed by the economic crisis of 2008.

In the preceding studies presented in Table 2, bibliometric variables were another type of variable capable of explaining technology adoption. Fig. 7 indicates the correlations between the market share and two variables, patent applications and news exposure. Unlike in the case of search traffic, the comparison of the intensities of the patent application rate and of news coverage was based on observations made from 2002 to 2010, because the activities of the producers or the media may take place in advance. The intensity of the patent application rate was found to follow a trend quite similar to that of the sales rate, while by contrast the intensity of the news coverage did not have any significant correlation.

4.2. Results of observing the correlation between the sales rate and the variables for each respective search unit

To conduct a comparative study of the search units, first the traffic for technology searches and the traffic for searches

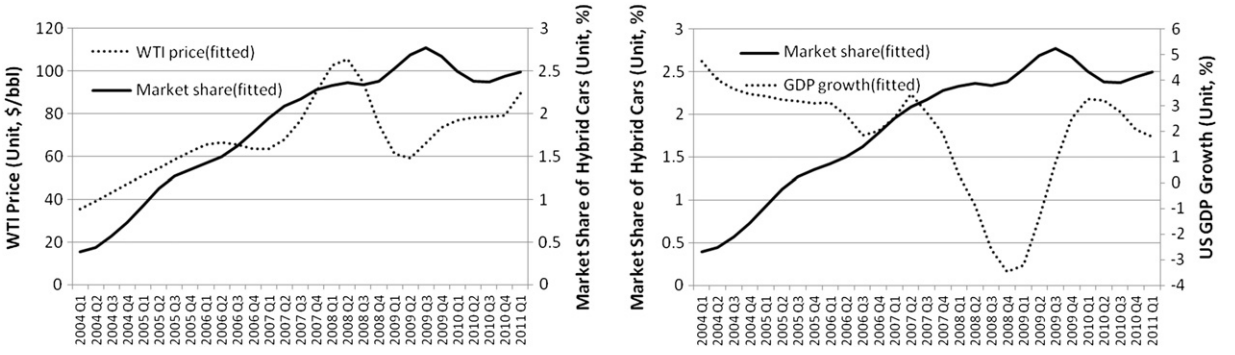

Fig. 6. Comparison of the market share of hybrid cars in the U.S. (quarterly data) to WTI oil prices (left) and the GDP growth rate (right). Source: EIA, U.S. Department of Commerce & Hybridcars.com, 2011. 6. (modified).

specifying the brand name Prius (hereinafter referred to as "brand search") were compared, and the results are shown in Fig. 8. Note that Fig. 8 expresses the relative intensity for the brand name in a manner reflecting the scale of the search volume. In Fig. 8, we see that technology searches followed an overall trend of decrease with the exception of the period in 2008 marked by a rapid rise in the WTI price, while by contrast, brand searches increased overall.

Fig. 9 presents a comparison of the sales rate for hybrid cars with the respective traffic for technology searches and brand searches. The traffic for searches made for hybrid cars followed a clearly identifiable trend of decrease from 2008, as explained in regards to Fig. 5, while by contrast, the traffic for Prius brand searches was closer in trend to the sales rate. This allowed us to judge that brand searches, compared to searches for the technology (or the category of product), are better indicators of the process of new technology adoption when approaching the decision to purchase.

Meanwhile, Fig. 10 presents the results of comparing the traffic for searches that include key attributes, namely price and mpg, simultaneously along with the technology name. The searches simultaneously including mpg continued relatively steadily without fluctuation, but responded more markedly to environmental factors such as a rapid rise in the WTI price. In contrast, compared to searches which only specified the technology name, the traffic for searches which simultaneously specified price information showed a lesser degree of decrease in the number of searches from 2008.

The trend of increase in traffic for searches simultaneously including price as shown in the left figure of Fig. 10 is seen to be closer to the sales rate according to the right figure of Fig. 10. In other words, these results allow us to deduce that the correlation to sales will be higher in the case of the traffic for searches simultaneously specifying price rather than traffic for searches including only for the technology name.

Fig. 11 presents the results of comparing the traffic for searches that included representative attributes such as price or mpg along with the brand name. Although in general the results were sensitive to environmental factors such as steep rises in WTI prices as seen in Fig. 10, an overall trend of increase was observed in the case of mpg. Also, the traffic for searches that included specifications for the price had a higher level of recent traffic overall, compared to the traffic for searches that only included the brand name.

Moreover, Fig. 11 demonstrates that the tendency of recent traffic to be higher in the case of searches that included both the brand name and price compared to the traffic for searches based only on the brand is connected to the tendency of searches simultaneously specifying both the brand name and the price to follow a trend very similar to the sales rate. In other words,

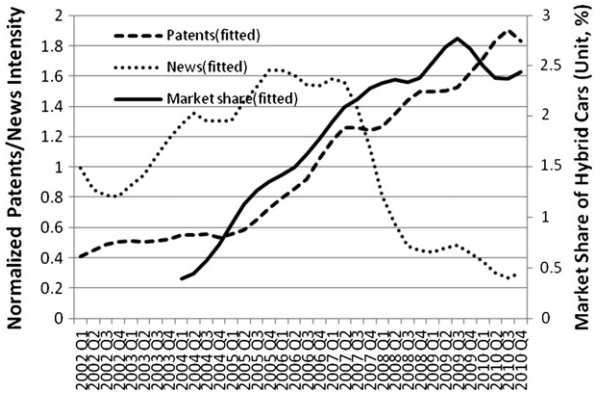

Fig. 7. Comparison of patent application rate, news coverage and market share. Source: USPTO, Google news archive & Hybridcars.com, 2011. 6. (last accessed).

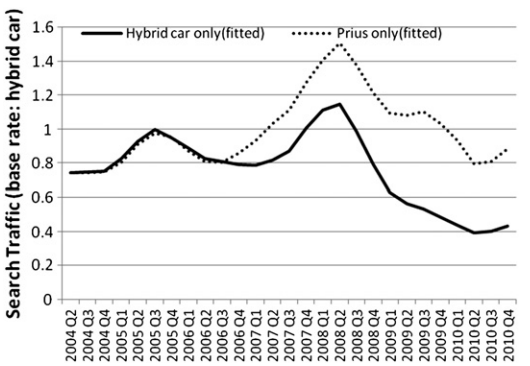

Fig. 8. A comparison of technology vs. brand searches. Source: Google insights, 2011. 6. (last accessed).

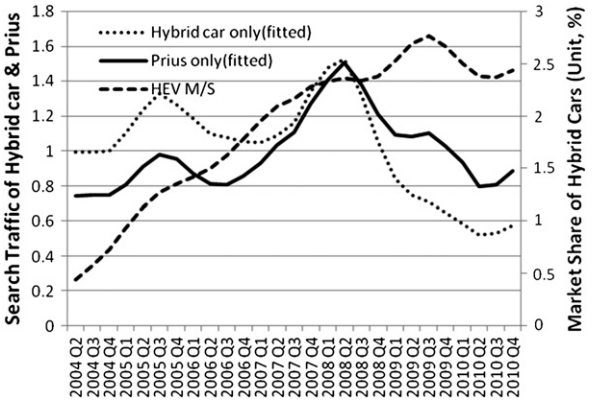

Fig. 9. Comparison of the sales rate to the traffic of technology searches and brand searches.
Source: Google insights & Hybridcars.com, 2011. 6. (last accessed).

these results lead us to deduce that the traffic for searches that simultaneously specify price has a higher correlation to sales, compared to searches that specify only the brand name.

4.3. Model verification

Table 4 presents the outcome of verifying the hypotheses for the research model explained earlier in Fig. 2 and summarizes the results of the simple regression analysis conducted on time series data for which the dependent variable is the sales rate of hybrid cars (HEV). The time series regression analysis was conducted using the ARIMA(1,0,0) model, in consideration of the autocorrelation of the data. Although analysis was also performed on the ARIMA(2,0,0) model or the ARIMA(1,0,1) model, etc., the ARIMA(1,0,0) model was determined to be the most superior in terms of explanatory power and significance probability. The minimum of the R-square was 87.5%, demonstrating a very high level of explanatory power overall, and the minimum for the Ljung & Box value was 0.984, which was much greater than 0.05 and therefore significant [21]. As regards the parameters of the ARIMA model, the significance probabilities for AR(1) were all 0.000, demonstrating a high degree of significance. Moreover, the stationarity requirements were all satisfied as well.

According to the results of analysis based on the above model, the independent variable having the most significant relation to the sales rate of hybrid cars was the traffic of searches in which both the name 'Prius' and the price were included, and the traffic for searches using the product brand name (Prius) was also found to have a significant correlation to the sales rate. These demonstrated superior explanatory power compared to various macro-indices or bibliometric indices that had been identified as having partial significance in preceding studies. Fig. 12 presents a comprehensive summation of the results of the above regression analysis in relation to the research model and the hypotheses presented in Fig. 2.

Table 4 can be adequately explained by the hypotheses verification results of the research model explained in Fig. 2, but it is limited in its ability to determine the forecasting ability of variables regarding the sales rate. Therefore, to review the possibility that combinations among multiple variables may affect changes in explanatory power, we proceeded to perform additional multiple regression analysis. Table 5 summarizes the results of multiple regression analysis of time series data in which the hybrid car (HEV) sales rate is the dependent variable. For the representative variable of search traffic, we used the traffic of simultaneous searches for the Prius and price, which appeared to have the highest significance in the comparison shown in Table 4, and we analyzed together the variables of WTI prices, patents, news, and GDP growth indices, which we compared in terms of significance with search traffic. The multiple time series regression analysis was analyzed likewise using the ARIMA(1,0,0) model, considering the data's auto-regression. The R-square was 94.5%, which represented a slight increase compared to the 93.2% shown in Table 4. The Ljung & Box value was 0.985, which was significant since it was much larger than 0.05 [21]. The ARIMA model parameter showed that the significance probability of AR (1) was 0.000, indicating a high level of significance.

The above results of analysis based on the multiple regression analysis model demonstrated that search traffic and patent applications together had a significant correlation to the hybrid car sales rate. These results remained identical even when news, GDP growth and WTI were eliminated one by one through backward elimination. R-square, which had been 93.2% in Table 4, increased to 94.5% in Table 5, and when only search traffic and patent applications were left remaining by

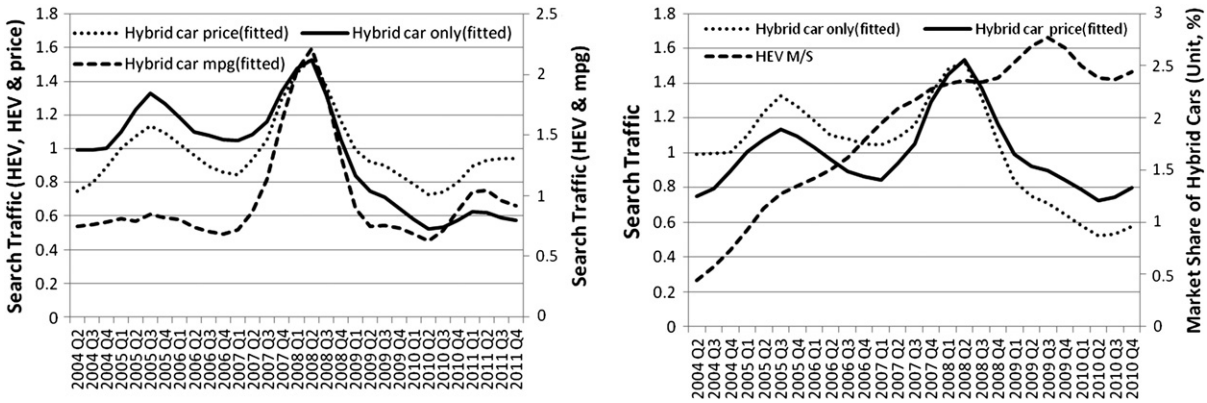

Fig. 10. Comparison of the search traffic (left) and the market share (right) to the traffic for technology searches.
Source: Google insights & Hybridcars.com, 2012. 1. (last accessed).

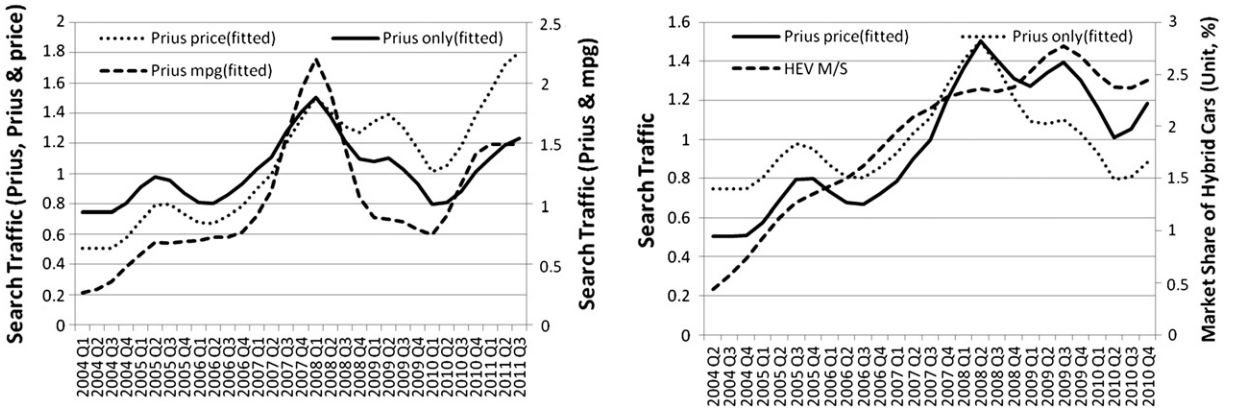

Fig. 11. Comparison of the search traffic (left) and the market share (right) to the traffic for brand searches.
Source: Google insights & Hybridcars.com, 2012. 1. (last accessed).

means of backward elimination, the R-square was found to rise up to 96.8%. According to Table 4, the sales rate can be explained by search traffic, but Table 5 demonstrates that we can increase explanatory power by taking the patent application into consideration simultaneously.

5. Discussion

The results of this research challenge us with questions on three key issues, which we will examine in further detail below. First, what is the reason that the traffic of technology searches fails to exhibit a significant correlation with the sales rate? Secondly, why does the traffic of brand searches have a significant correlation to the sales rate? Thirdly, although the sales rate was not greatly influenced by environmental variables excluding patents, would there also have been an influence on search traffic?

5.1. The absence of significant correlation between sales and the traffic of technology searches

The lack of significant correlation between sales and the traffic of technology searches is an issue that can be explained from several perspectives. The first possible explanation is to attribute this lack of correlation to the failure of the product's innovation to fulfill the anticipation raised by the interest in the new technology. The incongruence between interest and behavior cited above can thus be blamed on the level of satisfaction regarding the product or its quality, but it is also possible to offer an explanation based on the essential characteristics that the consumer exhibits toward the technology. The surface phenomenon whereby the traffic of searches conducted by users (consumers) decreases even during the period of growth within the life cycle when market sales are actually on the increase can also be explained by means of the technology hype cycle. In the technology hype cycle model, the trough of disillusionment is generally explained as being caused by disappointing experiment results, technological problems, declining interest among the media, the backlash arising from excessive media exposure, or insufficient infrastructure for usage [22,23]. Because hybrid cars rely on the same infrastructure as conventional cars, namely the internal combustion engine, the likely cause would be that the mpg improvement was below expectations or that media exposure had declined, rather than infrastructural problems or the effects of "marketing hype."

Considering the dynamic nature of information searches conducted by consumers as shown in Fig. 1, it is also possible to explain that the rising level of comprehension among the masses regarding the universal set reached a peak in 2005, and thereafter there was a decrease in the use of the term 'hybrid car,' which is also the name of the product category. Since the

Table 4
Results of the ARIMA regression analysis performed on the research model's hypotheses.

Variables	Hypotheses	R2	Ljung–Box	Statics		
				Beta	t−value	Significant
HEV only	H_0 A1	0.875	1.000	0.147	0.597	0.556
HEV & prince	H_0 A2	0.887	1.000	0.284	1.184	0.248
HEV & mpg	H_0 A3	0.885	1.000	0.044	0.375	0.711
Prius only	H_0 A1-1	0.898	1.000	0.592	2.298*	0.031
Prius & price	H_0 A2-1	0.932	1.000	0.764	3.623**	0.001
Prius & mpg	H_0 A3-1	0.892	1.000	0.123	1.020	0.318
WTI price	H_0 DI	0.892	0.999	0.002	0.709	0.485
GDP growth	H_0 E1	0.881	1.000	−0.006	0.222	0.826
News	H_0 BI	0.881	1.000	0.002	−0.008	0.994
Patents	H_0 C1	0.924	0.984	0.507	0.996	0.329

* Significant at the 5% level.
** Significant at the 1% level, ARIMA(1,0,0,)(0,0,0) by SPSS 20.0.

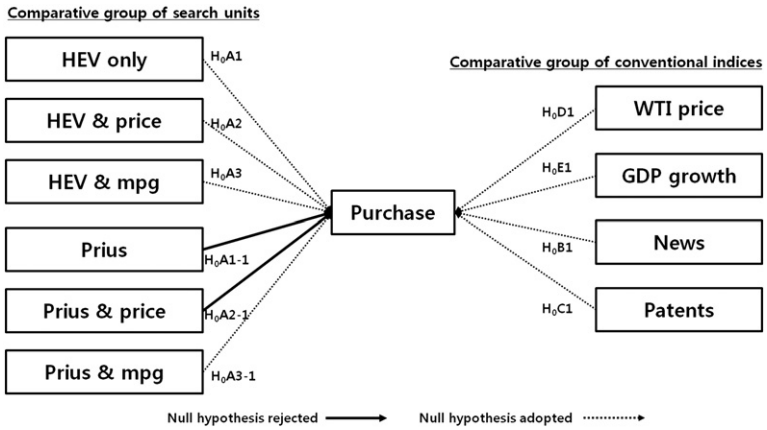

Fig. 12. Verification results for the hypotheses presented in the research model.

term 'hybrid car' is not only the name of the technology but also the term used for the category of product, the decrease in the use of this term after reaching a peak in 2005 can be attributed to the fact that the masses no longer experienced the need to approach their searches starting from the universal set.

Meanwhile, from the perspective of the Bass Diffusion Model, we can seek an explanation based on the possibility that a critical mass had been reached that enabled a change in communication channels [24]. In other words, there was a diffusion of interpersonal channels that determined purchasing decisions, bypassing the need for media exposure or active searches conducted by users. However, because there has recently been a recurrent increase in search traffic, we will need additional observations of values before drawing our conclusions. Also, we will need to further examine the question of whether the use of interpersonal channels in the recent internet environment necessarily results in decreasing search traffic, since the distribution of information via the web is precipitating a shift from mass media channels to interpersonal channels.

Thus, based on various theoretical grounds, we can explain that the changes in interest among users may become reflected in changes in their information searching activities and that the human response toward the new and novel exhibits a bell curve, in which the initial positive responses indicate an early rise in passion and then is followed by negative responses indicating disappointment.

5.2. The significance of the correlation between brand search traffic and the sales rate

According to the outcome of our research regarding the search units of the search traffic, we judged that the traffic data for searches specifying the brand name or searches specifying both the brand name and the price as shown in Fig. 11 can be utilized effectively for forecasting sales volume in the context of new technology adoption. The possibility of using this data for brand forecasting has already been confirmed by Choi & Varian [15], though such forecasts remained limited to corporate brands. Also, Su [20] has already verified that the searches for information regarding price is one of the major contents responsible for increases in search volume. While preceding studies had regarded the use of search traffic as a highly promising method for forecasting, in this present study, we found the forecasting ability of data on searches that use the technology name to be limited. The difference is that the approach in preceding studies was based on search keywords such as companies or search categories, while the present

Table 5
Estimated ARIMA model fit statistics and the parameters of the sales rate.

Model fit statistics				Ljung—Box Q(18)		
Stationary R-squared	R-squared	RNISE	MAPE	Statistics	Df	Significant
0.945	0.945	0.182	10.641	6.888	17	0.985

Variables	Estimates	Beta	t-value	Significant
AR1	0.988	0.025	39.549**	0.000
Patents	0.696	0.241	2.894**	0.009
News	0.328	0.250	1.312	0.204
WTI price	−0.003	0.003	−0.920	0.368
GDP growth	−0.015	0.025	−0.576	0.571
Search traffic (Prius & price)	0.997	0.236	4.22	0.000

**Significant at the 1% level, ARIMA(1,0,0,)(0,0,0) by SPSS 20.0.

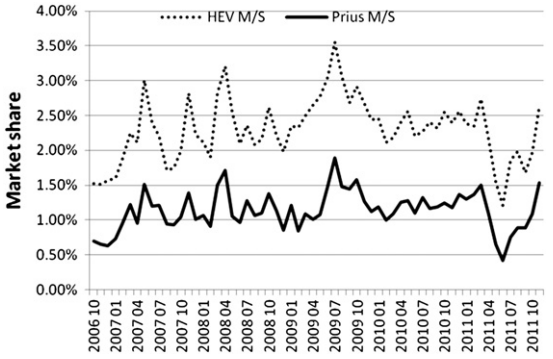

Fig. 13. Comparison of changes in the market share of hybrid cars and Prius. Source: Hybridcars.com, 2012. 1. (last accessed).

research targets the traffic data for searches that specified the name of a new technology or the product category. It was therefore necessary to comparatively examine the unit of the keyword used in the searches in order to determine whether the differences between the results of preceding studies and those of our present research were due to the object of searches, and to enable us to better utilize the search traffic as a variable in the future.

We therefore analyzed as our independent variable those cases in which the keyword unit of the searches was Prius, the leading brand. We conducted a regression analysis on the traffic of searches for Prius and its significant correlation to the sales rate of hybrid cars can be attributed to two factors. First, as explained above, the users who conduct searches for the product brand tend to have a higher level of prior knowledge and are psychologically closer to making a purchasing decision compared to users who conduct searches for the technology name or the product category. The second important factor was that Prius is a product that has attained a representative status within the category of hybrid cars. The Prius enjoys absolute market dominance, since the cumulative sales percentage of the Prius has reached nearly 50% of the total sales of hybrid cars, and as shown in Fig. 13, the sales trend is also very similar. The sales rate of the Prius presented in Fig. 13 analyzes the percentage of the total sales of new cars occupied by Prius sales.

5.3. Differences between the factors influencing brand search traffic and sales rate

As shown in Table 4 and Table 5, although environmental variables do not have a large influence on the sales rate, it is possible that they influenced search traffic. If, as we argue in this study, search traffic is a variable that effectively explains the information searching and evaluation process in the consumer behavior model, then the factor that affects consumers' behavior in information searches may differ from the factors that influence their purchasing activities. To explain this issue, we conducted a multiple regression analysis on exogenous variables that affect search traffic.

Table 6 summarizes the results of the multiple regression analysis performed on time series data in which the dependent variable is the traffic of simultaneous searches for Prius and price information. The multiple time series regression analysis was conducted using the ARIMA(2,0,0) model, considering the auto-regression of the data. The R-square was the high percentage of 97.8%, and the Ljung & Box value of 0.102 was also significant, being greater than 0.05 [21]. As for the ARIMA model parameters, both the parameters for AR (1) and AR (2) had a significance probability of 0.000, indicating high significance.

The analytical results above, obtained from the multiple regression analysis model, demonstrated that the WTI price has a significant impact on search traffic. Although the WTI price did not have a direct influence on the HEV sales rate, we confirmed that it did have an influence on search traffic. We therefore verified that the WTI price can indirectly affect sales by influencing consumers' search activities. A rise in WTI price increased consumers' interest in hybrid cars, but this increased WTI price did not become directly reflected in the sales rate.

Synthesizing the results of Tables 5 and 6, we were able to confirm that among the conventional indices, patent applications can be used to estimate the 'increase in sales due to technological innovation' or the 'increase in R&D investment due to increase in sales,' and that the WTI price can influence consumers' search activities. We were thus able to explain why significance had been found in preceding studies. The particular significance of our own study is that we have demonstrated search traffic to be a variable with superior explanatory power compared to such conventional indices that assist

Table 6
Estimated ARIMA model fit statistics and the parameters of Prius & price searches.

Model fit statistics				Ljung-Box Q(18)		
Stationary R-squared	R-squared	RMSE	MAPE	Statistics	Df	Significant
0.978	0.978	0.053	4.025	23.444	16	0.102

Variables	Estimates	Beta	t-value	Significant
AR1	1.683	0.119	14.206**	0.000
AR2	−0.883	0.150	5.891**	0.000
Patents	0.260	0.155	1.681	0.108
News	−0.056	0.103	−0.549	0.589
WTI price	0.010	0.003	3.888**	0.001
GDP growth	0.025	0.023	1.073	0.295

**Significant at the 1% level, ARIMA(2,0,0,)(0,0,0) by SPSS 20.0.

indirectly or directly in forecasting consumers' purchasing behavior, as shown in Table 4.

6. Conclusion

Our present study has important implications for those who wish to utilize search traffic when analyzing the adoption of new technologies or new products. Although the traffic for technology searches demonstrated a low degree of significance for explaining sales, the traffic for brand searches was highly significant in correlation to sales volume. This indicates that if the unit of the search is properly selected, search traffic can serve as an extremely useful method for analyzing or forecasting sales volume. It is worth emphasizing that that search traffic data demonstrated superior explanatory power compared to indices that were used in the past to forecast demand, such as the GDP growth rate, the WTI price, patent applications and news coverage. Of course, it must be granted that this conclusion is merely the statement of the implications deduced from on a single case study, and hence it cannot yet be generalized to apply to all cases. Although there is a limitation to how far we may generalize on the basis of this case study, it is clear that this study offers various meaningful implications to consider in regards to the practice of using search traffic to analyze the adoption of products or technologies.

Brand search traffic was found to be capable of explaining the purchases of adopters, a phenomenon that had been difficult to explain based solely on the traffic of technology searches. Specifically, this study also demonstrated that the traffic for searches in which price is simultaneously included also has a highly significant correlation to sales. This significant correlation between the brand and the sales rate for products based on new technology can also be explained in terms of the dynamic nature of information searches conducted by consumers. In Fig. 1, where hybrid cars constitute the universal set, we see that searches based on the brand name, which constitutes the awareness set or the consideration set, cannot help but explain purchases to a higher degree compared to technology searches. In addition, construal level theory also explains the fact that simultaneous searches for prices were found to have a greater explanatory power relative to simultaneous searches for mpg. Whereas mpg is a factor that approaches the desirability of the product's features, price is a factor that determines the ease or difficulty of making the purchase and therefore the feasibility of its purchase, and it is for this reason that the searches specifying is highly capable of explaining purchases [25]. Of course, the fact that the brand Prius enjoyed an absolute dominance in terms of its share in the hybrid car market was another important factor.

As emphasized in preceding studies, search traffic enables us to make real time verifications and to conduct investigations closely approaching the population, and it is also superior in forecasting ability. Moreover, search traffic has the particular advantage of allowing us to identify hidden aspects of users that is difficult to reveal through survey-based research. Nonetheless, there are also definite disadvantages. Trends driven by affective responses such as excessive obsession regarding celebrities or the rapid dissemination of fears create a major drawback when utilizing search traffic. For this reason, search traffic may not be the most effective analytical method for all types of social phenomena. However, as the results of the present research demonstrate, this data does have clear advantages for analyzing the adoption of new technologies or new products. This study has found that search traffic does indeed exhibit superior explanatory ability in the analysis of new technology adoption when compared to indices that had been previously used to preceding studies to forecast demand.

If efforts are made to further refine our use of search traffic by adjusting the unit of searches, for example, we anticipate that our discovery of the promising potential of using search traffic as an index for forecasting and analyzing the adoption of new technology will make both significant scholarly and practical contributions to various fields that utilize forecasts. Observing the actual on-line behavior of consumers is the most reliable way of tracking the changing topography of consumer use and identifying what they consider important during specific time periods.

We anticipate that the implications of our present study will provide positive guidance for those analyzing information regarding consumer behavior, as such information becomes available in ever more diverse forms with the advent of the big data era. If the results and methods of this research are used as the foundation for further empirical studies regarding the various industries and types of innovation, this will contribute to enhancing the objectivity and explanatory power of diverse analyses and forecasts using search traffic. Furthermore, we believe that this research can also be used for consumer behavior modeling employed in various fields such as marketing, which will facilitate efforts to establish actual corporate strategies such as the construction of marketing strategies.

One limitation we experienced was due the nature of the data used in this research. Although Google provided the source data and abundant information pertinent to research methods in regards to the search traffic data, nonetheless we were restricted by the fact that the search traffic data used in this study consisted only of processed secondary data. Another limitation was that our research relied solely on search traffic provided by one particular site, namely Google. Although Google currently dominates the market, it is possible that the expanded use of SNS such as Facebook may result in shifting the categories of users that utilize Google. For this reason, in future studies it will be necessary to conduct a comparative analysis using search traffic provided by other search engines for the purpose of analyzing the characteristics of Google's users.

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