Economic Valuation of a New Meteorological Information Service: Conjoint Analysis for a Pollen Forecast System

JOONG-WOO LEE

Department of Management/IIMR, Inje University, Gimhae, Gyeongsangnam-Do, South Korea

JINYONG JANG

B&MC Korea (Booz & Company Seoul Office), Seoul, South Korea

KWANG-KUN KO

Department of Management/IIMR, Inje University, Gimhae, Gyeongsangnam-Do, South Korea

YOUNGSANG CHO

Department of Information & Industrial Engineering, Yonsei University, Seoul, South Korea

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ABSTRACT

This study aims to investigate the public's preferences for and quantitatively measure the economic value of a pollen forecast system, a new meteorological information service, in South Korea. To directly measure the economic value of the pollen forecast system and its attributes in terms of the public's preferences, this study used conjoint analysis and a discrete choice model. In the conjoint survey, seven factors were considered as attributes of the pollen forecast system: the forecast area, forecast interval, information type, forecast period, delivery media, forecast accuracy, and price. Based on survey data from the six largest metropolitan areas in South Korea, the authors estimated people's utility function by a rank-ordered logit model and calculated the relative importance (RI) and marginal willingness to pay (MWTP) for each attribute. People considered price, meaning the additional tax burden, to be the most important attribute, with a relative importance of 42.3%. In descending order of relative importance, price was followed by forecast accuracy, forecast interval, forecast area, forecast period, and information type; these attributes had MWTP values of 0.133, −0.017, 0.098, 0.059, and 0.011 USD month^{-1}, respectively. The results of this study can serve as guidance of government investments in the pollen forecast system and provide an empirical basis for the application of conjoint analysis to economic valuation studies on a wider range of meteorological information services.

1. Introduction

A meteorological information service is a type of service that provides the public or specific users with information on the state of the atmosphere, such as temperature, rainfall, wind speed, and snowfall. Such services can be subdivided by domain, such as climate forecasts and weather forecasts (Freebairn and Zillman 2002). Climate forecasts track long-term phenomena using knowledge accumulated over years, while weather forecasts mainly focus on short-term meteorological phenomena (Nguyen and Robinson 2014). With the growing impact of various meteorological phenomena, the scope of meteorological information services has expanded to include such issues as the concentration of ozone, yellow dust, and pollen. Recently, a pollen forecast service has received much attention because pollen is known to have a significant impact on public health and worker productivity. Pollen is regarded as a natural air pollutant and a leading cause of allergy-related illnesses such as asthma, rhinitis, and conjunctivitis through contact with the nose and eyes (Lewis et al. 1983; Esch and Bush 2003). Moreover, pollen affects

Corresponding author address: Youngsang Cho, Department of Information & Industrial Engineering, Yonsei University, 50 Yonsei-Ro, Seodaemun-gu, Seoul 120-749, South Korea.
E-mail: y.cho@yonsei.ac.kr

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worker productivity in a wide range of industries that require outdoor activity, such as leisure, construction, or shipbuilding (Eggen et al. 2013). Recognizing the seriousness of its impact on public health and worker productivity, European countries such as the United Kingdom and Germany have developed pollen forecast services. South Korea is also considering developing a pollen forecast system.[1]

Developing a new meteorological information service requires significant investment in new meteorological observation infrastructure, high-performance computer systems, and other areas. While public meteorological information service is, in a sense, a quasi-public good,[2] the segment of the public that benefits from the infrastructure investment does not participate in the investment process (Anaman et al. 1995). Therefore, in the situation that most countries provide public meteorological information services by a government-sponsored institution, government has a crucial role in the development and implementation of a new meteorological information services. To provide justification for government investment, it is important to quantitatively measure the effect of meteorological information services on the public's quality of life and social welfare. In this context, there has been much research aimed at estimating the economic value of meteorological information. Most of these studies, however, have focused on the potential cost avoidance in specific industries or society, and the use of valuation methods based on public preferences remains insufficient. Before the early 2000s, it was difficult to find studies that directly estimated the economic value of meteorological information services and their technical attributes from the perspective of public preferences (Rollins and Shaykewich 2003). More recently, some studies have attempted to utilize this approach (Lazo et al. 2010; Nguyen and Robinson 2014). However, it remains insufficient considering the growing interest in meteorological information and the number of meteorological information services.

The purpose of this study is to quantitatively measure the economic value of a meteorological information service based on public preferences. To that end, we conducted an empirical investigation of a pollen forecast system, a new meteorological information service that the Korea Meteorological Administration (KMA) is preparing to develop. Pollen information is gathered and generated by KMA financed by government tax revenue, and it is consumed by the general public without additional payment or by the specific user groups for their business purposes with a usage-based fee. Because the KMA is considering a pollen forecast system to be used by the general public, this study focuses on public preferences rather than specific users' profit maximization decision making. To measure the economic value of a pollen forecast system in South Korea, this study employed conjoint analysis, a statistical method widely used in new product/technology development and marketing. This method enables us to identify people's preferences regarding each attribute of a pollen forecast system and to measure the system's economic value based on utility theory.

2. Previous literature

Given the increasing interest in the socioeconomic impact of meteorological phenomena, there have been many efforts to estimate the economic value of meteorological information and the meteorological information service such as weather forecast and climate forecast services. Most previous studies have measured the economic value of meteorological information using the cost-avoidance method. In the cost-avoidance method, the meteorological condition is regarded as an uncertain input that affects the production activity of certain industries; producers make decisions under this uncertainty for their profit maximization or cost minimization. In this approach, the economic value of meteorological information services is estimated by modeling the effect of marginal changes in forecast accuracy (regarded as reductions of uncertainty) on the specific production process (Rollins and Shaykewich 2003). With this approach, many studies have focused on the possible impact of meteorological information on productivity changes or cost reduction in weather-sensitive industries such as agriculture (Katz et al. 1982; Tice and Clouser 1982; Adams et al. 1995; Fox et al. 1999), aviation (Leigh 1995; Allan et al. 2001; Latorella and Chamberlain 2002; Keith and Leyton 2007), and transportation (Thornes and Davis 2002; Skarpness et al. 2003; Leviäkangas et al. 2007). Other studies have focused on the socioeconomic impact of weather disaster forecast systems such as flood (Day 1970) and wildfire (Sol 1994; Gunasekera 2005) forecast systems.

Some researchers, meanwhile, have explored the value of meteorological information services in a broader sense, not limiting their investigation to specific industries. These studies have used diverse methodological approaches to assess such information's economic value. Thornes and Stephenson (2001) assessed the economic

[1] In this paper, the term "pollen forecast system" indicates more than a mere forecast of pollen itself. Rather, it encompasses the whole system required for such a service, including the provision of pollen information according to region and time, as well as forecast and delivery of pollen information to the public and particular consumers.

[2] Lazo et al. (2008) argued that weather forecasts are quasi-public goods because of their nonrival and limited-excludability nature.

value of weather forecasts by proposing a value index that considered the cost–loss ratio and forecast errors. They defined three attributes of weather forecast quality—reliability, accuracy, and skill—and assessed value through the cost–loss ratio, applying it to a road weather forecast system. Freebairn and Zillman (2002) developed an overall framework for assessing the economic value of meteorological services. With this framework, they reviewed various approaches to measuring the economic benefits of meteorological services and suggested four appropriate methodologies for use in valuation studies: market prices, normative or prescriptive decision-making models, descriptive behavioral response models, and the contingent valuation method (CVM). Rollins and Shaykewich (2003) emphasized the necessity of demand-based valuation methods and applied the CVM to estimate people's willingness to pay (WTP) for meteorological information services via an automatic audio system. Leviäkangas (2009) used a theoretical approach to assess the value of meteorological information from the perspective of value engineering and pricing techniques. He disaggregated the information value into attributes with descriptive contents and proposed that the sum of the attributes' values can be regarded as the value of meteorological information.

With regard to the economic valuation of pollen information or a pollen forecast system, past studies have not examined the economic value of pollen information itself. Instead, most previous research has focused on the effects of various air pollutants on public health. These studies estimated the economic value of information of the air pollutants based on people's WTP to maintain their health or based on costs incurred from diseases related to air pollution. Crocker et al. (1979) analyzed the effect of air pollution on mortality rates using dose-response functions and calculated the economic value of air pollution control systems based on interview data on peoples' WTP for reducing mortality rates. In addition, Loehman and De (1982) calculated people's WTP for reducing health risks related to air pollution using a binary choice method. After identifying the health effects of air pollution from power plants, they presented respondents with two policy scenarios involving decreased income and increased health status, with respondents choosing the scenario in which they would be better off. Alberini and Krupnick (2000) estimated the economic value of improved air quality using the cost of illness (COI) and WTP methods. The COI is a commonly used method to estimate economic costs based on income losses and medical expenses associated with illness (Hodgson and Meiners 1982). Another commonly employed method is work loss days (WLDs), which estimates the relationship between lost work days and air pollution data; Ostro (1983) analyzed the health effects of air pollution using this method.

As the above discussion shows, most studies on the economic value of meteorological information have intended to provide estimations of potential cost reductions in specific industries or of the potential impact on society (Rollins and Shaykewich 2003). Studies that have investigated the value of meteorological information more broadly, not focusing on specific industries, have given limited consideration to the public's preferences for various attributes of a meteorological information service. Public preferences, however, are an important part of successfully implementing such a service. In particular, it is important to analyze which attributes of such services people regard as important and how their utility changes according to changes in these technological attributes. Thus, we regard conjoint analysis as a useful method to identify the important attributes of new meteorological information services and to estimate their economic value from the perspective of public preferences. Two recent studies applied conjoint analysis to estimate the economic value of meteorological information services (Lazo et al. 2010; Nguyen and Robinson 2014). These studies estimated the economic value of improving the forecast accuracy of existing weather forecast services, including hurricane forecasting and an early warning service for tropical cyclones. However, we could find no studies that applied conjoint analysis to estimate the economic value of a new meteorological information service.

3. Methodology

Conjoint analysis is widely used in various fields including marketing (Green and Srinivasan 1990; DeSarbo et al. 1995), transportation (Hensher and Greene 2001), and environmental studies (Hanley et al. 1998; Layton and Brown 2000). In conjoint analysis, hypothetical situations are presented to respondents to generate stated preference data for products or services that are generally not available in the market. Because respondents are asked to choose alternatives according to their preferences, conjoint survey data take on a discrete form. Therefore, the utility function is estimated by a discrete choice model rather than a general regression model. The discrete choice model is based on the random utility model, which assumes that consumers choose alternatives that maximize their utility. Based on the random utility model, the indirect utility, U_{ij}, that respondent i gains from choosing alternative j can be expressed as follows:

$$U_{ij} = V_{ij}(\mathbf{w}_i, \mathbf{x}_j) + \varepsilon_{ij} = \boldsymbol{\beta}'\mathbf{X}_{ij} + \varepsilon_{ij}. \quad (1)$$

This indirect utility is divided into two parts: deterministic and stochastic. Deterministic utility, V_{ij}, is obtained from the alternative's attributes, and stochastic utility, ε_{ij}, is the utility from unknown stochastic factors. The deterministic utility is affected by the socioeconomic variables of respondent i and the technical attributes of alternative j, which are expressed by $\mathbf{w}_i$, and $\mathbf{x}_j$, respectively (Train 2009).

In general, survey respondents are asked to choose the most preferred alternative, to rank their preferences among several alternatives, or to give a score to each alternative. While the best method for conducting a conjoint survey depends on the research topic and purpose, Calfee et al. (2001) argue that rank-ordered data are more useful than most-preferred-choice data because the former can provide more information for parameter estimation. Therefore, in this research, we asked survey respondents to rank their preferences among alternatives, and a rank-ordered discrete choice model was used for the estimation of consumers' utility function.

When respondent i ranks J alternatives as $r_i = \{r_{i1}, r_{i2}, \ldots, r_{iJ}\}$, the probability of this response can be expressed as $\Pr(r_i) = \Pr[U_i(r_{i1}) > U_i(r_{i2}) > \cdots > U_i(r_{iJ})]$. If we rearrange this equation, it can be expressed as follows:

$$
\begin{aligned}
&\Pr[U_i(r_{i1}) > U_i(r_{i2}) > \cdots > U_i(r_{iJ})] \\
&= \Pr[U_i(r_{i1}) > U_i(r_{ij}) \quad \text{for} \quad j = 2, \ldots, J] \\
&\quad \times \Pr[U_i(r_{i2}) > U_i(r_{ij}) \quad \text{for} \quad j = 3, \ldots, J] \\
&\quad \times \cdots \times \Pr[U_i(r_{iJ-1}) > U_i(r_{iJ})] \\
&= \prod_{h=1}^{J-1} \left[\frac{e^{V_{ih}}}{\sum_{m=h}^{J} e^{V_{im}}} \right] = \prod_{h=1}^{J-1} \left[\frac{e^{\boldsymbol{\beta}'\mathbf{X}(r_{ih})}}{\sum_{m=h}^{J} e^{\boldsymbol{\beta}'\mathbf{X}(r_{im})}} \right], \qquad (2)
\end{aligned}
$$

where $X(r_{ih})$ represents the attributes of the h th ranked alternative of respondent i.

In this study, we use the rank-ordered logit model for analyzing the rank-ordered data. The logit model assumes that each distribution of an error term follows an independent and identically distributed (i.i.d.) Gumbel distribution so it can induce the closed form of the likelihood function, which makes the estimation relatively easy (Train 2009). The coefficients of the utility function can be estimated through the maximization of the log-likelihood function derived from Eq. (2), as follows:

$$
\begin{aligned}
L(\beta) &= \sum_{i=1}^{N} \ln \prod_{h=1}^{J-1} \left[\frac{e^{\boldsymbol{\beta}'\mathbf{X}(r_{ih})}}{\sum_{m=h}^{J} e^{\boldsymbol{\beta}'\mathbf{X}(r_{im})}} \right] \\
&= \sum_{i=1}^{N} \sum_{h=1}^{J-1} \boldsymbol{\beta}'\mathbf{X}(r_{ih}) - \sum_{i=1}^{N} \sum_{h=1}^{J-1} \left[\ln \sum_{m=h}^{J} e^{\boldsymbol{\beta}'\mathbf{X}(r_{im})} \right]. \qquad (3)
\end{aligned}
$$

Marginal willingness to pay (MWTP) refers to the amount of money people are willing to pay in order to maintain the utility level according to a unit of change in the quantity or quality of an attribute. Therefore, it can be interpreted as the compensated surplus change when the level of an attribute is marginally changed. Based on the estimates of attributes, the MWTP of a certain attribute t can be calculated as follows:

$$
\mathrm{MWTP}_{x_{jt}} = -\frac{\partial U_{ij}/\partial x_{jt}}{\partial U_{ij}/\partial x_{j\mathrm{price}}} = -\frac{\beta_t}{\beta_{\mathrm{price}}}, \qquad (4)
$$

where $x_{j\mathrm{price}}$ and β_{price} are the "price" attribute and its estimated coefficient, respectively (Hensher et al. 2005a,b), and x_{jt} and β_t are the attribute and its estimated coefficient of a certain attribute t, respectively.

4. Empirical analysis

a. Conjoint survey design

A pollen forecast system has many attributes that can affect the public's usage and satisfaction levels. Therefore, it is necessary to identify the important attributes and convert them into measurable economic variables. In conjoint analysis, the number of attributes is closely related to the reliability of the research (Wittink and Cattin 1989). According to Green and Srinivasan (1978), respondents have difficulty evaluating objects when there are more than six attributes. However, other studies pointed out that the median number of attributes used in conjoint analysis is six to eight in practice (Cattin and Wittink 1982; Wittink and

TABLE 1. Attributes of the pollen forecast system and their levels.

Attributes	Variables	Levels
Forecast area	X_{Area}	1: Dong-nae area* 0: Broad area
Forecast interval	X_{Interval}	3, 6,12 (h)
Information type	X_{Type}	1: Actual concentration figure 0: 5 levels
Forecast period	X_{Period}	1: Today (1 day) 2: Today–tomorrow (2 days) 3: Today–the day after tomorrow (3days)
Delivery media	X_{Media}	1: Mass media and Internet 0: SMS and e-mail
Forecast accuracy	X_{Accuracy}	50, 70, 90 (%)
Price	X_{Price}	100, 500, and 1,000 (KRW month^{-1})**

* *Dong-nae* is a Korean word that means small village. In South Korea, the Dong-nae forecast is a digital local forecast providing weather information for a village (30 km × 30 km sized area) at 3-h intervals. The KMA has provided this service since September 2009. Currently, the Dong-nae forecast contains weather information such as the probability of precipitation, amount of precipitation, temperature, wind, and humidity.

** 1,000 Korean Won (KRW) was equivalent to approximately 0.77 USD on average in 2009, so 100, 500, and 1,000 KRW month^{-1} is equivalent to 0.08, 0.38, and 0.77 USD month^{-1}, respectively.

Cattin 1989). Following these studies, we considered seven attributes in this study. To identify the important attributes in a pollen forecast system, we reviewed the previous literature, relevant reports, and news articles, and we conducted interviews with experts. By these means, we selected the following attributes: forecast area, forecast interval, information type, forecast period, delivery media, forecast accuracy, and price. Table 1 shows the attributes considered in the conjoint survey and their levels.

First, the "forecast area" refers to the physical area for which pollen information is provided. We considered two levels of forecast area: "broad area" and "Dong-nae area." Broad area refers to pollen information provided at the city or province level, while Dong-nae area refers to pollen information provided at the town or village level. The latter level provides information at finer spatial scales, with more microinformation. Before examining the estimation results of the empirical analysis, we expected that respondents would prefer Dong-nae area information over broad area information.

Second, the "forecast interval" refers to the time interval between pollen information updates. For this attribute, we considered three levels: 3, 6, and 12 h. For example, a 3-h forecast interval means that the KMA updates the pollen information every 3 h. Prior to the actual analysis, we anticipated that consumers' utility would increase as the forecast interval became shorter.

Third, the "information type" is the format in which the pollen concentration level is presented. Two formats were considered: a five-level format and an actual concentration figure. The five-level format presents pollen concentration information as one of five discrete levels: none, a little, normal, slightly strong, and very strong. The actual concentration figure presents pollen information in units: the measurement of the number of pollen grains in a cubic meter of air. In general, the five-level format has the advantage that people can more easily understand the seriousness of the pollen concentration and take appropriate precautions. For the actual concentration figure, we thought it possible that only people with experience of a pollen-related illness would recognize the seriousness of the concentration; the actual figure is not the type of information that an ordinary person readily understands. Therefore, before the actual analysis, we did not expect the public to prefer this format.

Fourth, the "forecast period" indicates the time period covered by the pollen forecast. For this attribute, we considered three levels: 1 day, 2 days, and 3 days. In other words, the KMA would provide the pollen information for "today," "today and tomorrow," or "today, tomorrow, and the day after tomorrow." Beforehand, it was expected that people would prefer longer periods of pollen information.

Fifth, "delivery media" refers to the distribution channel through which the pollen information is delivered. We considered two delivery methods, the first being mass media and the Internet; using this method, pollen information is delivered through mass media such as TV, newspapers, and radio, as well as the KMA website. This method is currently used in most countries, including South Korea, for the delivery of general meteorological information. The second distribution channel considered is short message service (SMS) and e-mail. Using this method, pollen information is delivered directly through SMS via mobile phones or e-mail at specified times. This attribute is directly related to respondents' consumption behavior with regard to information and devices. Therefore, it was expected that people's preferences regarding this attribute would vary according to the ways in which they use information technology (IT) services.

Sixth, "forecast accuracy" means the level of consistency between forecasted information and the actual pollen count. Here, we considered three levels: 50%, 70%, and 90%. It was generally expected that respondents would express a preference for higher forecast accuracy.

Seventh, and last, the attribute "price" refers to the amount people are willing to pay for the use of a pollen forecast system. In conjoint analysis, MWTP can be calculated by including a price attribute as a payment vehicle. Therefore, an appropriate payment vehicle

TABLE 2. Example of a conjoint survey card.

Attribute	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Forecast area	Broad area	Dongnae area	Dongnae area	Broad area
Forecast interval	6 h	6 h	12 h	3 h
Information type	Actual concentration figure	Actual concentration figure	Actual concentration figure	5 level
Forecast period	Today (1 day)	Today (1day)	Today–the day after tomorrow (3 days)	Today (1 day)
Delivery media	Text message and e-mail	Mass media and Internet	Mass media and Internet	Mass media and Internet
Forecast accuracy	70%	90%	50%	50%
Price (KRW month^{-1})	1,000	100	1,000	100
Preference order				

should be considered to ensure the proper measurement of MWTP. We considered the monthly national health insurance premium as a payment vehicle because it is related to health and has a quasi-tax nature. In the conjoint survey, we informed participants that launching this new public information service would involve a required cost, which would be shared by the public in the form of an increase to the monthly tax (the national health insurance premium). As people are generally reluctant to accept an increase in taxes, it was expected that respondents would express a negative preference regarding the price attribute.

Once the attributes and their levels were determined, a set of hypothetical choice alternatives were created. Theoretically, 648 choice alternatives can be derived from the combination of the levels of seven attributes ($2 \times 3 \times 2 \times 3 \times 2 \times 3 \times 3 = 648$). As it would be difficult for respondents to express their preference for all alternatives, we used a fractional factorial design that ensured orthogonality between each attribute. Through this process, we obtained 16 alternatives and made four choice sets; each set contained four alternatives. In the survey, respondents were asked to rank their preferences among the four alternatives in the four choice sets. Table 2 shows an example of the conjoint cards that were used in the survey.

The conjoint survey was conducted through online in October 2009 by a market research company.[3] The total number of respondents was 402. The respondents, who were from the six largest metropolitan areas in South Korea, were selected through stratified random sampling by gender and region to reflect the demographic characteristics of the Korean population. The total number of respondents was set at about 400 before conducting the survey, and the target respondents were selected based on region and gender from lists that the company already possessed. First, the market research company sent an e-mail to target respondents asking about their willingness to participate in the survey. Those who agreed accessed the survey through a website. If the target number of responses was not reached, the e-mail was sent to an additional sample pool according to region and gender. This process was repeated until the target number of responses was reached for each region and gender.

Table 3 presents the demographic statistics of survey respondents in terms of gender, age, residence area, and their occupation. Because the survey respondents were selected through stratified random sampling by gender, age, and residence area, the percentage of survey respondents in each subcategory presents similar share of the Korean population for each subcategory.[4] According to the Statistics Korea website (http://kostat.go.kr/portal/english/news/1/17/1/index.board?bmode=download&bSeq=&aSeq=273109&ord=2), the number of the Korean population is approximately 49 411 000 in the year 2010, and the share of males is about 50.1% (24 758 000). The people whose age is from 15 to 60 occupy 68.4% (33 779 000) of the entire Korean population. Among them, the portion of people whose ages were in the following ranges: 15–19, 20–30, 30–40, 40–50, and 50–59 are shown as 10.3% (3 467 000), 20.7% (7 001 000), 24.1% (8 128 000), 25.2% (8 507 000), and 19.8% (6 676 000), respectively. In terms of residential area, the people living in the six metropolitan cities account for 44.8% (22 114 000) of the total population. Among six metropolitan cities, Seoul appears to have the highest proportion, 43.5% (9 631 000), followed by Busan, Incheon, Daegu, Daejeon, and Gwangju, Ulsan as 15.3% (3 393 000), 11.9% (2 632 000), 11.0% (2 431 000), 6.7% (1 490 000), and 6.6% (1 466 000), respectively. As shown above and Table 3, the percentage of population in each

[3] The attributes and their levels were described and defined for respondents during the online survey. This information was displayed on the screen, and the page was controlled to prevent the next page from appearing for a certain duration to give respondents adequate time to read the description of attributes and levels.

[4] The percentage of each subcategory is calculated based on the sum of the population of each category.

TABLE 3. Demographic statistics of survey respondents.

Category		Statistics
Gender	Male	202 (50.2%)
	Female	200 (49.8%)
Age	15–19	39 (9.7%)
	20–30	102 (25.6%)
	30–40	106 (26.4%)
	40–50	89 (22.1%)
	50–59	65 (16.2%)
Residence area	Seoul	191 (47.5%)
	Busan	60 (14.9%)
	Incheon	43 (10.7%)
	Daegue	41 (10.2%)
	Deajeon	26 (6.5%)
	Gwangju	24 (6.0%)
	Ulsan	17 (4.2%)
Occupation	Office worker	167 (41.5%)
	Housewives	55 (13.7%)
	College student	55 (13.7%)
	Self-employed	34 (8.5%)
	Middle/high school student	26 (6.5%)
	Others	65 (16.2%)
Previous experience visiting hospital	Yes	133 (31.1%)
or pharmacy because of pollen	No	269 (66.9%)

category is similar to those of survey respondents, so it is found that the survey respondents are well selected to reflect the characteristics of the Korean population. Regarding previous experience with a pollen-related illness, 33.1% of respondents said that they had visited a hospital or pharmacy because of a pollen-related illness.

b. *Estimation results*

To estimate people's preferences regarding a pollen forecast system, a utility function is constituted focusing on the technical attributes of the system as follows. The variables used in the utility function are described in Table 1:

$$U = \beta_{\mathrm{Area}}X_{\mathrm{Area}} + \beta_{\mathrm{Inverval}}X_{\mathrm{Interval}} + \beta_{\mathrm{Type}}X_{\mathrm{Type}} + \beta_{\mathrm{Period}}X_{\mathrm{Period}} + \beta_{\mathrm{Media}}X_{\mathrm{Media}} + \beta_{\mathrm{Accuracy}}X_{\mathrm{Accuracy}} + \beta_{\mathrm{Price}}X_{\mathrm{Price}} + \varepsilon \quad (5)$$

In this utility function, U indicates the utility gained from the pollen forecast system, and the coefficient of each variable shows the marginal effect of each variable on the utility. The coefficients of the utility function were estimated using the NLOGIT program. Table 4 summarizes the estimation results obtained from the 402 respondents.

As shown in Table 4, the coefficients of all variables except β_{Media} are significant at a 1% significance level. The coefficient β_{Area} has a positive value, meaning that people prefer to receive a forecast for Dong-nae rather than broad area. This result is consistent with our expectation. The coefficient $\beta_{\mathrm{Interval}}$ shows a negative value, meaning that people's utility for the pollen forecast system decreases as the time interval for pollen information delivery increases. In other words, people prefer quick provision of the most up-to-date pollen information. The positive sign of the coefficient β_{Type} indicates that people prefer the actual concentration figure over the five-level format. The coefficient β_{Period} also has a positive sign, which implies that people prefer the 3-day forecasting period over the day-by-day forecast. The positive sign of the coefficient $\beta_{\mathrm{Accuracy}}$ is also consistent with our expectation; this result indicates that people prefer a more accurate information service. The coefficient β_{Price} has a negative sign, which is also consistent with our expectation; this indicates that price increase reduces people's utility. As the price attribute is set to be a tax in this study, it implies that people are reluctant to accept an increase in taxes.

The fifth column of Table 4 shows the relative importance (RI) of each attribute of a pollen forecast system. The RI of each attribute is the percentage of

TABLE 4. Estimation results of meteorological pollen forecast system (with total sample).

Coef	Estimate	Ratio	p value	Relative importance	MWTP*	95% confidence interval of MWTP*
β_{Area}	0.205**	5.594	0.000	8.129%	0.133	(0.084, 0.185)
$\beta_{\mathrm{Interval}}$	−0.026**	−3.164	0.002	9.158%	−0.017	(−0.028, −0.006)
β_{Type}	0.152**	4.198	0.000	6.006%	0.098	(0.051, 0.147)
β_{Period}	0.091**	3.762	0.000	7.171%	0.059	(0.029, 0.088)
β_{Media}	0.029	0.781	0.435	1.132%	0.019	(−0.029, 0.066)
$\beta_{\mathrm{Accuracy}}$	0.017**	15.867	0.000	26.150%	0.011	(0.009, 0.012)
β_{Price}	−0.001**	−21.798	0.000	42.254%		

* The unit of MWTP is USD month^{-1}. At the time of the survey, the price attribute levels were presented in KRW, so that the unit of MWTP was calculated as KRW month^{-1}. However, in this paper, we report the MWTP estimation results as USD month^{-1} to make them easily understood by international readers.

** Significant at the 1% significance level.

TABLE 5. Estimation results of respondents visiting a hospital because of pollen.

Coef	Estimate	t ratio	p value	Relative importance	MWTP[a]	95% confidence interval of MWTP[a]
β_{Area}	0.216[b]	3.404	0.001	8.778%	0.150	(0.061, 0.256)
β_{Interval}	−0.030[c]	−2.158	0.031	11.168%	−0.021	(−0.043, −0.002)
β_{Type}	0.123[c]	1.964	0.050	4.985%	0.085	(0.002, 0.179)
β_{Period}	0.061	1.456	0.146	4.937%	0.042	(−0.015, 0.099)
β_{Media}	0.086	1.348	0.178	3.493%	0.060	(−0.028, 0.148)
β_{Accuracy}	0.016[b]	9.030	0.000	26.201%	0.011	(0.008, 0.015)
β_{Price}	−0.001[b]	−11.791	0.000	40.437%		

[a] The unit of MWTP is USD month^{-1}.
[b] Indicates significance at the 1% significance level.
[c] Indicates significance at the 5% significance level.

utility range in relation to the total variation (Seo 2005). In other words, the RI indicates people's perceived importance of certain attributes compared to other attributes. The RI of i attribute is calculated as follows:

$$\frac{\mathrm{RI}_i = \widehat{\beta_i}\ (\mathrm{Max}_{\mathrm{Level}_i} - \mathrm{Min}_{\mathrm{Level}_i})}{\sum_{i=1}^{J} \widehat{\beta_i}\ (\mathrm{Max}_{\mathrm{Level}_i} - \mathrm{Min}_{\mathrm{Level}_i})}, \tag{6}$$

where $\widehat{\beta_i}$ indicates the estimate of attribute i and $(\mathrm{Max}_{\mathrm{Level}_i} - \mathrm{Min}_{\mathrm{Level}_i})$ means the difference between the maximum and minimum levels of attribute i. The results indicate that people consider price (i.e., the additional tax burden) to be the most important attribute, with 42.3% of RI. Forecast accuracy is regarded as the second-most important attribute, with 26.2% of RI, followed by forecast interval and forecast area, whose RIs are 9.2% and 8.1%, respectively. Because the RI represents the public's perceived importance of attributes when using the pollen forecast system, it provides very important information to service providers seeking to meet people's expectations. Thus, the RI results can be viewed as a prioritized list of technological developments that are necessary from the perspective of public preferences. The KMA, in preparing its pollen forecast system, can refer to these results as a guide for the development of technology.

The MWTP results are presented in the sixth column of Table 4. The data show that people are willing to pay 0.011 USD month^{-1} for improving the forecast accuracy by 1%. The fact that the MWTP is negative for the forecast interval indicates that each person is willing to pay an additional 0.017 USD month^{-1} in order to reduce the time interval for updating the pollen forecast by 1 h. With regard to the forecast area, each person is willing to pay an additional 0.133 USD month^{-1} to change this attribute from broad area to Dong-nae area. For the forecast period, people are willing to pay an additional 0.059 USD month^{-1} to extend the forecast period for 1 day. Regarding information type, individuals are willing to pay an additional 0.098 USD month^{-1} to change from five-level information to the actual concentration figure. The estimated MWTP results can be compared with some kinds of household expenditures. To do so, we considered the TV license fee, which is regarded as a public information service and financed by government tax revenue (Leviäkangas 2009). In South Korea, each household is charged 2,500 KRW (1.92 USD) as a monthly TV license fee. Therefore, the MWTP estimation results for each attribute of the pollen forecast system relative to the TV license fee are as follows: 6.9% (forecast area), −0.9% (forecast interval), 5.1% (information type), 3.1% (forecast period), and 0.6% (forecast accuracy).

Because point estimation generally involves inherent uncertainty, presenting a confidence interval as well as point estimates is plausible in terms of showing embedded uncertainty. Therefore, a 95% confidence interval for MWTP is presented. This was calculated by the Monte Carlo simulation method proposed by Krinsky and Robb (1986) and Park et al. (1991). We first drew a sample from the multivariate normal distribution and repeated the sample drawing process until 5000 samples were obtained. Then, we calculated 5000 MWTPs based on the drawings and listed them in descending order. Finally, we excluded the smallest and largest 2.5% of all MWTPs. The last column of Table 4 shows the confidence interval for the MWTPs obtained from this process.

A pollen forecast system is likely to be used differently by people who have experienced a pollen-related illness. Therefore, an additional analysis was performed for the 133 respondents who had previously visited a hospital or pharmacy because of a pollen-related illness. Table 5 shows the estimation results for this group. Compared to the full sample, respondents who had visited a hospital or pharmacy because of a pollen-related illness expressed a higher relative importance and MWTP regarding forecast area, forecast interval, and forecast accuracy. This result implies that, compared to the general public living in six metropolitan cities, people who have experienced a pollen-related illness place higher importance on the forecast area, forecast interval, and forecast accuracy.

5. Conclusions

Using conjoint analysis, this study investigated the economic value of a pollen forecast system, which is regarded as a public good. To derive people's utility function for such a system, we applied a rank-ordered logit model to conjoint survey data obtained from 402 respondents. Through empirical analysis, we estimated the effect of each attribute of the pollen forecast system on people's utility and calculated the RI and MWTP of each attribute.

According to the results, people considered price (the additional tax burden) to be the most important factor in a pollen forecast system, with forecast accuracy being the most important technical attribute. In descending order of RI, these were followed by the attributes of forecast interval, forecast area, forecast period, and information type. The estimated MWTP values for different attributes were as follows: 0.133 USD month^{-1} (forecast area), -0.017 USD month^{-1} (forecast interval), 0.098 USD month^{-1} (information type), 0.059 USD month^{-1} (forecast period), and 0.011 USD month^{-1} (forecast accuracy). Respondents who had visited a hospital or pharmacy because of a pollen-related illness expressed a higher RI for forecast area, forecast interval, and forecast accuracy than the full sample.

Because a new pollen forecast system will cause an additional tax burden, decisions about the technical attributes of such a system should reflect people's preferences. When the system is being developed, these preferences will likely provide useful information in determining a proper combination of attributes. The estimation results of this study can provide useful information to service providers. When the KMA prepares the pollen forecast system with a limited budget, it can use the RI results to prioritize technology development according to the public's preferences. In addition, the MWTP result for each technical attribute can be interpreted as the public's economic benefit from a marginal improvement in that attribute. Therefore, these results can be utilized in cost-benefit analysis when developing such a service.

In order for a pollen forecast system to increase public benefits, it requires user-oriented features, such as plentiful content, a technical infrastructure, and new types of services tailored to certain user groups. To better utilize pollen information, the KMA should consider cooperating with industries whose productivity or sales of products are affected by pollen concentration. For example, firms that require extensive outdoor field production activities could cooperate with the KMA to develop an effective pollen information delivery system. In addition, pharmaceutical companies or drugstores can cooperate with KMA for their marketing activities such as an advertisement in the pollen information delivery channel through online or mobile services to promote the sales of pollen-related products: allergy medicine, masks, or eye drops, etc.

This study has several limitations. First, the estimation results may be biased by respondents' different levels of understanding of the questionnaire. We analyzed the public's preferences for a pollen forecast system through stated preference data due to the unavailability of revealed preference data. Although the definition of, and relevant information about, the pollen forecast system was provided to survey respondents, they may have had different perceptions and interpretations concerning the characteristics of the system, the definition of pollen, and the exact meaning of the questions. Thus, the estimation results may be over- or underestimated. In addition, the sample was limited, as the survey was conducted in only six metropolitan areas containing 44.8% of the total population of South Korea. Conducting face-to-face interviews with a nationwide sample might yield estimation results that reflect the real preferences of the public more closely. Despite these limitations, this research is significant in that it is the first use of conjoint analysis for a new meteorological information service. The advantage of conjoint analysis over other valuation methods, such as the contingent valuation method (CVM), is that it can provide information about the values of attributes that compose a meteorological information system. Especially in the development stage of a new meteorological information system, such information can offer guidance for prioritizing technology development and devising a price scheme for specific services according to public preferences. Despite this advantage of conjoint analysis, it has not yet been widely applied in the field of meteorology. In this regard, this research is expected to lay the groundwork for using conjoint analysis to estimate the economic value of a more diverse range of new meteorological information services.

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