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Deep sentiment analysis: Mining the causality between personality-value-attitude for analyzing business ads in social media

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ABSTRACT

IT vendors routinely use social media such as YouTube not only to disseminate their IT product information, but also to acquire customer input efficiently as part of their market research strategies. Customer responses that appear in social media, however, are typically unstructured; thus, a fairly large data set is needed for meaningful analysis. Although identifying customers' value structures and attitudes may be useful for developing targeted or niche markets, the unstructured and volume-heavy nature of customer data prohibits efficient and economical extraction of such information. Automatic extraction of customer information would be valuable in determining value structure and strength. This paper proposes an intelligent method of estimating causality between user profiles, value structures, and attitudes based on the replies and published content managed by open social network systems such as YouTube. To show the feasibility of the idea proposed in this paper, information richness and agility are used as underlying concepts to create performance measures based on media/information richness theory. The resulting deep sentiment analysis proves to be superior to legacy sentiment analysis tools for estimation of causality among the focal parameters.

1. Introduction

As part of their overall marketing strategy, modern businesses may choose to post tutorials, demos, lectures, workshops, and advertisements to social media such as YouTube or Facebook. Companies can then measure customers' responses on those social media as users post comments or recommendations. Automatic measurement of customers' opinions of or attitudes toward specific products and services may be possible using these comments, which often reveal customer preferences and values. This approach may be used as a marketing strategy to increase profits, identify target customers, and make efficient decisions about content.

However, in many cases, marketing managers have been unable able to show that social media is an effective tool for marketing purposes. This inability is related to the complexity of the data extractable from social media and the dearth of marketing analyses illustrating that social media can be an effective marketing tool. Big data tools may provide the answer to the first problem. Big data have been regarded as useful for analysis of data from social media, which are often excessive in volume, velocity, and variety. For example, key-value stores have been considered for quick processing of data extracted from YouTube (Cattell, 2011; Ghandeharizadeh & Yap, 2012; Stonebraker & Cattell, 2011). However, key-value stores, which have only the simplest data expression capability, are limited in their ability to interpret meanings correctly. In addition, YouTube videos are typically unclassified and provide non-standard information that is open to the public. Intelligent analysis of this kind of information is difficult (Nolan, 2012).

The purpose of this study is to propose a method of deep sentiment analysis that measures the causal relationships between customer attitudes, value structures, and personality while also automatically measuring customer responses to certain products on social media. Most current sentiment analysis tools provide only single- or double-layered sentiment structures characterized by sentiment polarity and/or categorized by personal profile. In addition, they do not consider how the sentiment polarity was calculated and the implications of the calculation method. By contrast, the proposed method offers a three-layer (deep) approach to customer attitude analysis. We herein describe the structure of a newly created personality–value–attitude (PVA) model. This new method combines an algorithm that identifies attitudes by finding keywords related to likes or dislikes from comments with an inference mechanism based on a socio-technical model that recognizes customer core values. The validity of this method was

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tested in an empirical analysis using actual comments made on YouTube about IT solutions and content.

2. Literature review

2.1. Social media for market sensing

Social media is a new way through which people are able to search and share information (Akar, 2011). Today, businesses routinely utilize social influence marketing and advertisement programs to identify customers and communicate their philosophy. They also run social media pages to build familiarity and advertise their goods through steady communication with their customers (Mangold & Faulds, 2009).

Social media facilitates marketing of products and services (Kaplan & Haenlein, 2010). Social media usually includes a feedback function, such as the "like" feature on Facebook and YouTube. When users "like" content related to a product or service, companies can learn what types of users are interested (Lipsman, Mudd, Rich, & Bruich, 2012). Social media also provides a forum for word-of-mouth as an effective marketing strategy. While a site operator can encourage visitors by encouraging them to post comments, a visitor can recommend the site by introducing its specific information to friends, which is often more effective.

The free video-sharing site YouTube is a social media forum in which users can directly upload or share video clips. As of 2012, it was operating in 54 languages across the world; it is a very influential web site. The rich content on YouTube videos and related texts is more easily shared than information shared using relatively limited texts and written documents. Larger and more diverse bodies of information can be acquired. If companies could collect dispersed multimedia information using links, information about video presenters or other related videos posted by other people could be easily acquired. YouTube's keyword search is a particularly effective tool for this purpose.

IT companies successfully utilize YouTube for marketing, communicating with customers, and predicting customer responses by introducing launched or imminent IT products in advance on YouTube. Showing other users experiencing IT products or software helps potential customers to recognize introduced products and can enhance intention to use. Although posting videos may invite critical comments, they can be considered customer feedback and used as important information to determine future customer needs. They may even provide insight as to how to craft messages or otherwise positively influence interactions with users.

2.2. Sentiment analysis

Sentiment analysis is a type of qualitative analysis (Wiebe, 1994) that focuses on identifying positive and negative opinions, emotions, and evaluations expressed in natural language (Wilson, Wiebe, & Hoffmann, 2009). It has gained importance as an analytical method in conjunction with natural language processing, providing more data for learning via the artificial intelligence technique and increasing the size of commercial intelligence applications (Cao, Thompson, & Yu, 2013). Rather than focusing on topic words as in classical text mining, sentiment signals are the main tools in sentiment analysis. These tools analyze the opinions of the writer directly, thereby avoiding costly and time-consuming content analysis (Pang & Lee, 2008).

In general, sentiment analysis proceeds according to the following process. First, each document (e.g., tweet, review, etc.) is tokenized into a word list by separating the elements in the document using whitespace and punctuation and accounting for common syntax found in the document (e.g., URLs and emoticons). Next, each token's log probability is identified in the word list. Since the word list is not comprehensive, some words can be ignored if they do not appear in the list. The log probabilities of each token are then added together to determine the probability of each sentiment (e.g., happy, sad) for the entire document. To improve the accuracy of sentiment analysis, a more comprehensive and accurate dictionary of positive and negative sentiments may be incorporated. However, sentiment analysis may involve use of simple word lists. For example, in a previous experiment, the initial word list was replaced with a sentiment score list generated using SentiWordNet (http://sentiwordnet.isti.cnr.it/), which consisted of over 400,000 words. If necessary, values can be averaged per a certain period of time (e.g., hour, day) to obtain a periodic sentiment value.

Algorithms used for sentiment analysis include naïve Bayes, maximum entropy, support vector machine, AdaBoost, and k-nearest neighbors, while data patterns used for sentiment analysis have taken the form of reviews or microblogs (Cao et al., 2013). Among the available algorithms, naïve Bayes can be used for both binary and multi-class classification problems for fast, highly scalable model-building and scoring. However, maximum entropy can combine different kinds of statistical dependencies into one unified framework, which helps to avoid the data sparseness problem common in language-related studies. However, none of the current algorithms has analyzed data in the form of continuous comments like those found on YouTube. Sentiment polarity has been limited to the level of judgments about positive or negative feelings and opinions. Causal analysis of these feelings and opinions has been lacking.

3. Deep sentiment analysis

3.1. The PVA model and deep sentiment analysis

In existing content or sentiment analysis, sentiment polarity is measured. Determining the cause of likes or dislikes remains the task of the decision-makers. For example, SentiWordNet appraises texts without explicit expression of likes or dislikes by combining the polarity of opinion sentences to assess subjectivity and objectivity of appraisals beyond measuring of sentiment polarity. This method is used to avoid simplistic conclusions (Esuli & Sebastiani, 2005). Nonetheless, SentiWordNet is unable to determine the causes of likes or dislikes.

In contrast, this study estimates the extent of likes or dislikes and related causal variables. As shown in Fig. 1, the core objective of this study is to develop a PVA model that shows causal relations

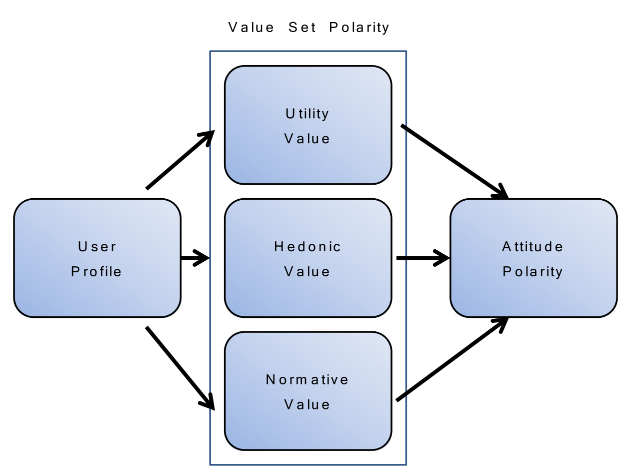


Fig. 1. PVA model (graphic representation of the proposed method).

between the following elements of the documents to be analyzed: user profile, value structure polarity, and attitude polarity. Attitude polarity shows the number of opinions about the source materials. Value structure polarity captures the value placed by the writers of such opinions on the source materials.

Value theory describes three categories of human values: utilitarian values, which emphasize usefulness, hedonistic values, which emphasize enjoyment, and normative values, which focus on the public good or social order. Since these values may manifest in various ways at the same time, the approach described here promotes an explanation in one dimension and then forms multidimensional polarity. That is, emphasis on a utilitarian value and its relation to liking or disliking a product does not necessarily mean denial of hedonistic values. In this study, text analytics are applied to assess the strength of these individual values.

In this study, personal profiles are acquired using commenters' networks on social media platforms. Though no personal information about users is obtained, information about interest areas is extracted through analysis of the characteristics of the posted videos, and aspects of personality are captured through analysis of the characteristics of the comments. Time of posting is also included in the profiles. Information about causal relations can also be extracted from accumulation of data about attitude polarity and value polarity, which can then be combined with information from user profiles.

3.2. Extraction from raw comments

Multiple viewers can post comments about videos introducing IT products. Comments can be short or very long; they tend to reveal the commenter's appraisals of the video and values, his or her likes/dislikes. The level of strength depends on the means of expressing values and likes/dislikes. For example, use of exclamation marks (e.g., !, !!!) or positive/negative adjectives (e.g., bad, stupid) implies a strong sentiment, while degree adverbs (e.g., completely, so, really) show the strength of commenters' values or attitudes. Several sample comments are provided below.

- "I want an i phonee soo bad!! (starskye111)"
- "My concern if I get the 4S, is that the apps might not be compatible with it anymore because of the 5s new screen.. they would make the screensize the "standard" for their apps.. or should I just go ahead?? (hoopdie)"
- "Completely agree!(kole hohenberger)"
- "Amazing sir. really helpful (soosoo1012)"
- "Im so happy with my smart phone:3(GunnerziithOo)".

These texts expressed on YouTube are rewritten as follows, using forms that can be acquired by analyzing source codes (parsing, lexical analyzing, etc.) open on YouTube.

```
<div class="content">
<div class="comment-text" dir="ltr">
<p>I ant an i phone soo bad!!</p>
</div>
<p class="metadata">
<span class="author ">
<a href="/user/starskye111" dir="ltr">starskye111</a>
</span>
<span class="time" dir="ltr">
<a dir="ltr" href="http://www.youtube.com/comment?
  lc=xxxxx"> 3시간 전 </a>
</span>
</p>
</div>
```

In the example above, starskye111 is a person with very strong intention to use the iPhone. His or her attitude towards other IT products or other YouTube videos may be acquired by clicking on the name (ID). In this example, we learn that this user likes an Android game and the Siri interface. Then, if we go to Siri, we are able to read comments about starskye111. A comment such as "Love it so much!:) from coolt15)" shows that coolt15 is a user who likes Siri. We are then able to see his favorite video clips and learn about other users' attitudes towards them. Thus, a chain reaction is created. We formalize the structure of these connections in Fig. 2 and in the following equation:

$$v = (pu, \{m|m \in M\})$$

where v indicates one of the videos from a set of videos, V. pu and m indicate specific persons from the set of posters $P(U)$ and comments posted about v, respectively.

Then, suppose that a certain comment m belongs to the entire set of comments M, and m comprises the video, commenter, and his or her values and attitudes toward the video. That is,

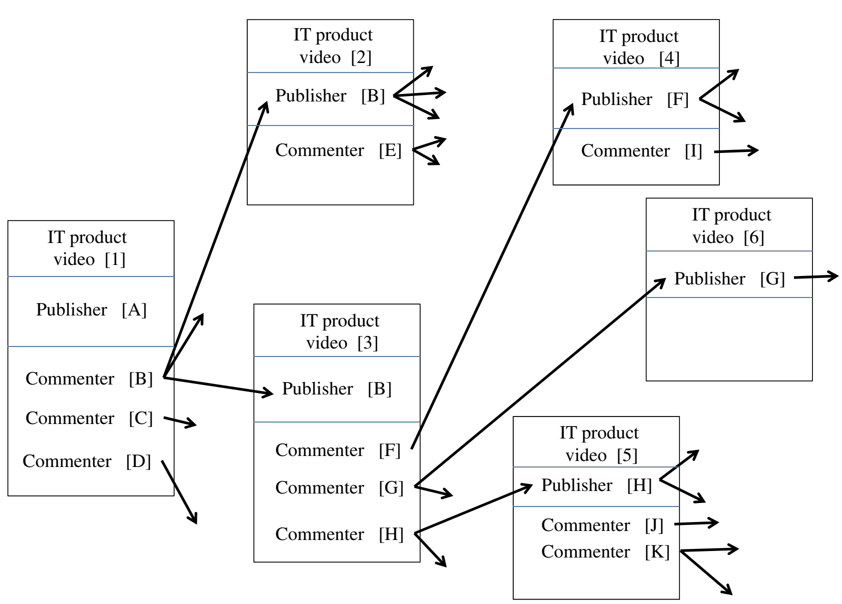


Fig. 2. Structure of big data due to connection of video and comments.

$$m = (v, pr, \tau, \alpha) \tag{1}$$

Here, pr, r, and α refer to a specific commenter, the commenter's value structure, and the commenter's attitude toward the video as shown in comment m, respectively.

Thus, videos about a certain product shown on YouTube are able to provide market segmentation data about how many people have what kinds of value structures and attitudes. That is, they can garner data as shown in (2). Then, we have $P = V$.

$$p = \{v\} = \{(pu, \{(v, pr, \tau, \alpha)\})\} \tag{2}$$

where p is a certain IT product that belongs to P on YouTube. Here, we are able to calculate the frequency of each (τ, α), which can be determined using big data tools. Finally, an entire set of users who posted comments or videos on YouTube can be represented as $P = P(U) \cup P(R)$.

3.3. Value set polarity

Value framework theory assumes that human values are not simple, but have multi-dimensional elements. Building on three universal requirements of human existence, Schwartz derived a two-dimensional bipolar structure with ten value types, as shown in Fig. 3 (Schwartz, 1992). Here, the two dimensions are openness to change vs. conservation, and self-enhancement vs. self-transition.

Once core values are established according to a value framework, researchers decide on corresponding items and related keywords using one of two possible methods: using the collective intelligence of ordinary people or experts, using model-based deduction, which involves construction of a social psychological model of items and value-related words extracted from the literature. In this study, we employed the latter method. In particular, we focused on value-related words used in product marketing on YouTube and words used in the marketing and management information systems fields, which are closely related to online marketing. For example, using value-related models in major marketing and management information systems, keywords for each construct and perceivable sentences or value-related words are collected. A sample value word list is shown in Table 1.

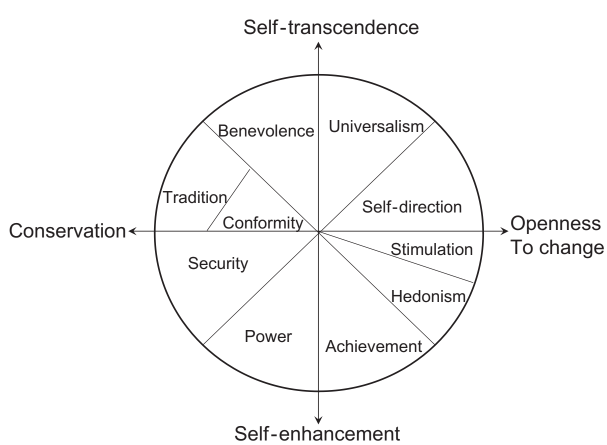


Fig. 3. Value structure (Schwartz, 1992).

The advantage of this method is that it overcomes the limitations of simple checking of likes/dislikes while measuring consumer preference using past web information, eventually facilitating measurement of more sophisticated preferences. Value becomes an important clue to explaining the cause of likes/dislikes. For example, while existing sentiment analysis methods merely infer likes/dislikes from the sentence "I do not like this product", the sentence itself does not directly show how the product may be improved, and no information regarding hedonic values such as fun and playfulness is provided.

3.4. Attitude polarity

Attitude is defined as "a mental position with regard to a fact or state" (Encyclopedia Britannica Online). Though attitudes may not be directly observable, they can be inferred from a person's objective, evaluative responses and comments. This is especially true with social media.

Attitudes shown on YouTube can be divided into two categories: attitudes towards specific videos, and attitudes towards the individual or company who posted the video. Attitudes towards videos are measured in this study by combining two methods: level of liking/disliking, as estimated by positive/negative words in the comments, and relevance, as estimated by comparing characteristics of other posted videos and their associated comments with specific videos earmarked for evaluation. However, measuring attitudes by this method is only valid for the target video under analysis.

In the analysis of attitudes towards videos, the level of liking or disliking shown in the comments must be estimated. Commenters' value structures can be revealed in their comments about how they like or dislike uploaded YouTube videos. For example, when people convey feelings of liking or disliking, they may use negative language that does not provide useful information to the original poster. In his treatise, Lange (2007) suggested that haters would express their opinions using very negative language and slang words that show contempt or insult in their comments. When commenters reveal their values or thoughts about videos, it is possible to infer $a(v_i)$ (the direction of liking/disliking) using the words contained within the comments. Here, v_i refers to the video being evaluated and $a(v_i)$ takes a value ranging from -1 (dislike) to 1 (like). For simplicity, likes and dislikes can be represented by three values: -1, 0, and 1, where 0 indicates an attitude in a comment that does not contain any opinions on the product.

The relation between any two randomly selected videos is calculated using consistently used keywords. Video contents can be estimated using three kinds of meta information: < meta name="keywords" content=" ">, < meta name="description" content=" ">, and < meta property="og:title" content=" "> from the YouTube documents. Here, with regard to v_i (video being evaluated) and v_j (video posted by the evaluator), the relation between two videos v_i, v_j, $r(v_i, v_j)$ is defined as the proportion of repeated keywords from the $n(v_i, v_j)$ aggregate of significant keywords

Table 1
Sample value word list.

Value	Value related item	Value word	Reference
Utilitarian	Perceived usefulness	Useful, less time, effective, efficient (more time)	Henderson and Divett (2003)
Utilitarian	Perceived ease of use	Easy	Henderson (2003)
Hedonic	Playfulness	Interesting, pleasant	Zhou, Fang, Vogel, Jin, and Zhang (2012)
Hedonic	Affective commitment	Happy	Zhou et al. (2012)

extracted from comments on the two videos, as in (3) below. However, repeated keywords in $n(v_i, v_j)$ are counted as one.

$$r(v_i, v_j) = \frac{c_{ij}}{n(v_i, v_j)} \tag{3}$$

Finally, attitudes towards specific videos are represented in (4).

$$\alpha_A(v_i) = \frac{1}{N} \times a(v_i) \times r(v_i, v_j) \tag{4}$$

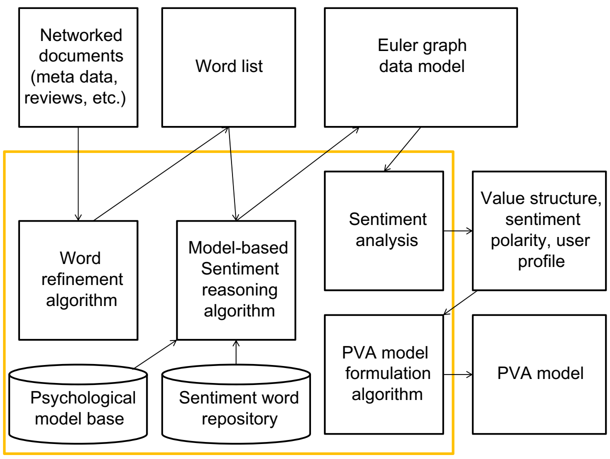


Fig. 4. System architecture.

Here, $1/N$ is a constant for normalization purposes.

Secondly, attitudes tend to be evaluated relatively consistently for videos posted by the same person, based on the assumption that the person who uploaded the video is the same regardless of uploaded content. For example, a commenter who might have particular political views tends to post negative comments regardless of the content of comments of persons with different political views merely because of their alleged different tendencies. For example, to those who support a given rival product (e.g., Android) against a user's preference (e.g., iPhone), the user may offer an opinion of "dislike" for the "other camp's" writings or videos regardless of its content. This distorts objective evaluation of the videos themselves because likes/dislikes about other posters cannot be distinguished from likes/dislikes about products or services shown on the videos. Thus, this effect must be deducted from the user's attitude towards the videos.

However, as shown by Lange (2007), this tendency is markedly more noticeable in haters, while persons who post favorable comments about a poster tend to post similar positive comments about the poster's video content. Thus, effects of attitude towards video posters may only be applied to dislikes. Ultimately, the result will be (5), as below.

$$\alpha_B(v_i) = \begin{cases} \frac{1}{N} \times a_A(v_i) \times r(v_i, v_j) & \text{if} \quad a_B(p_{m,n}) \geqslant 0 \\ \frac{1}{N} \times (a_A(v_i) - w(p_n) \times a_B(p_{m,n})) \times r(v_i, v_j) & \text{if} \quad a_B(p_{m,n}) < 0 \end{cases} \tag{5}$$

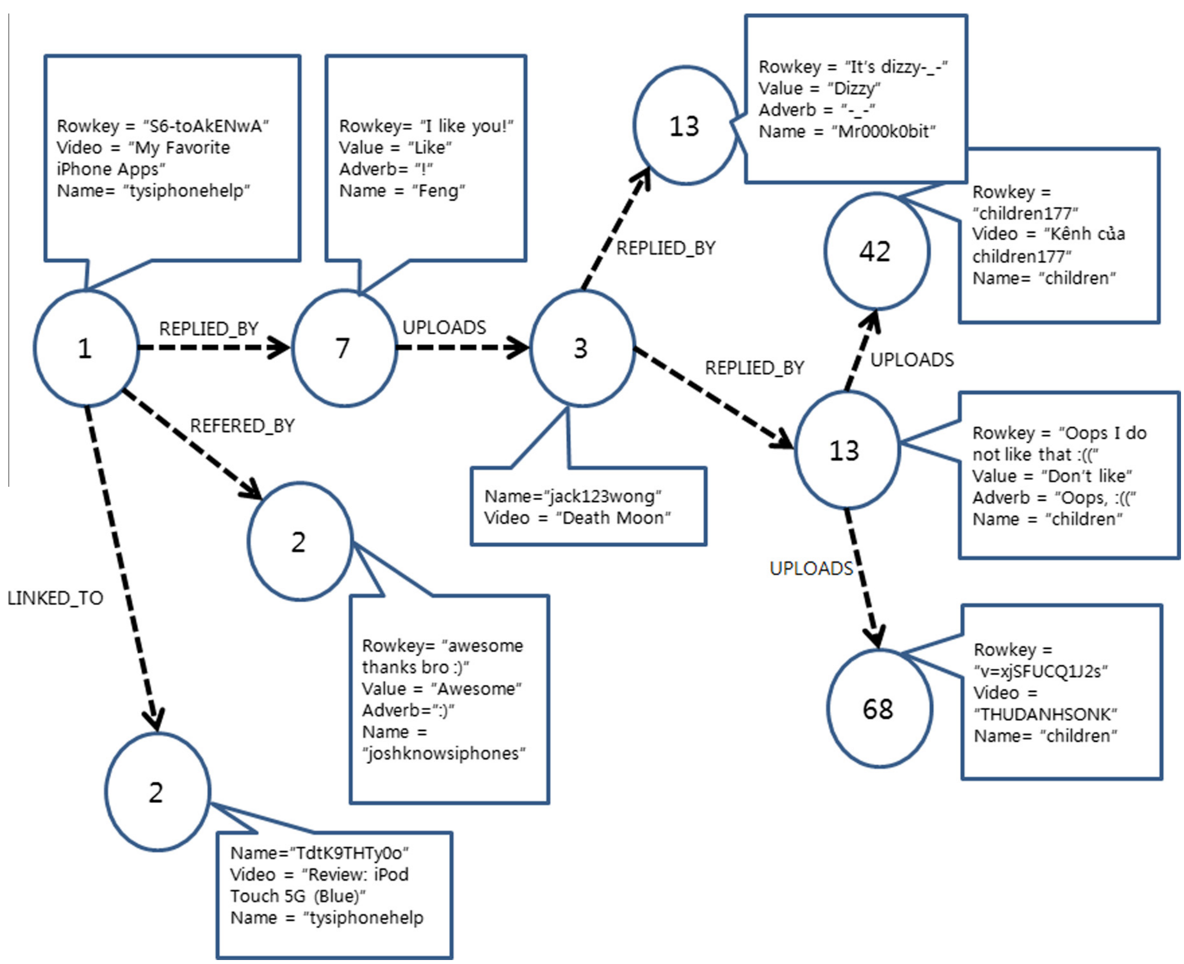


Fig. 5. Euler graph-based data model for scale analysis of video information on YouTube.

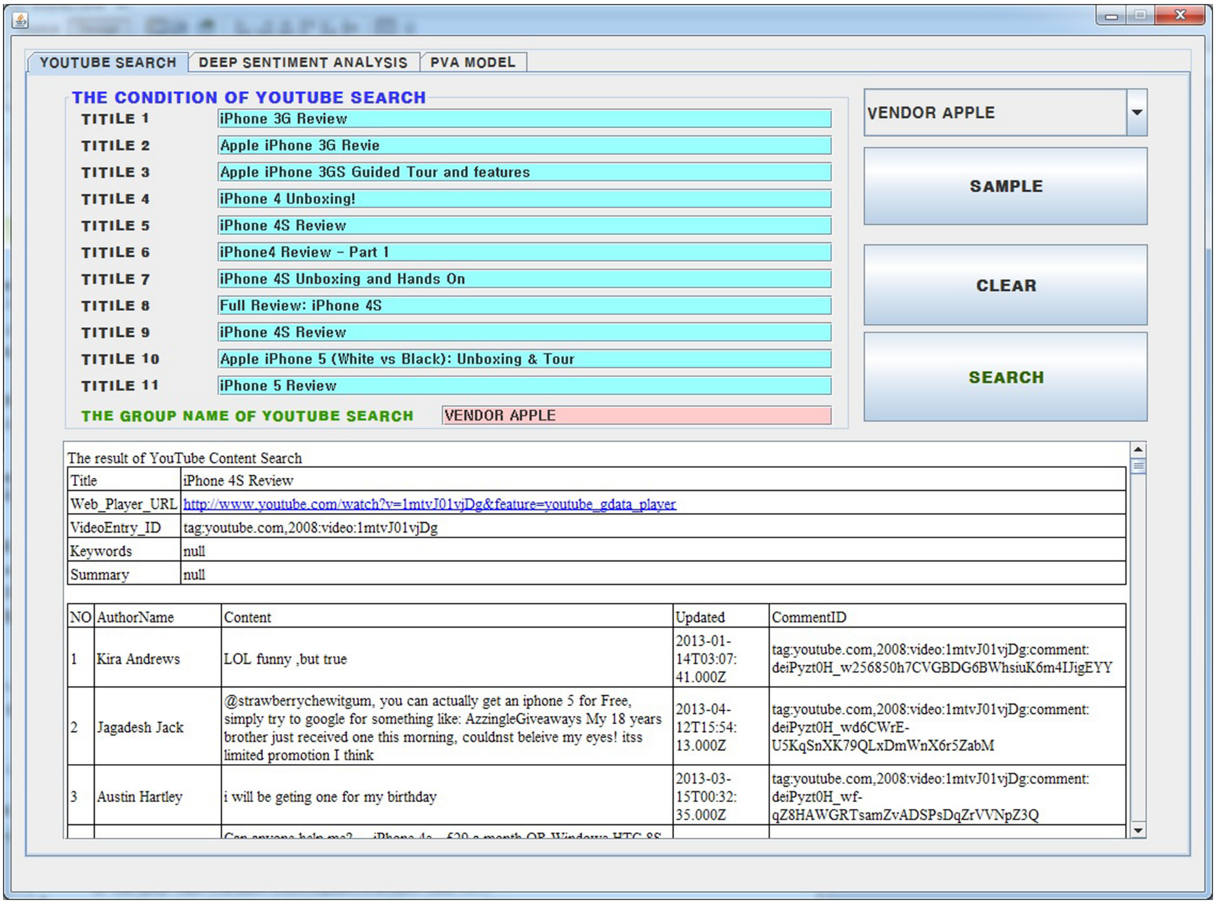


Fig. 6. YouTube video content collection process.

Here, $a_B(p_{m,n})$ means the level of likes or dislikes that an evaluator n has towards the poster m, while $w(p_n)$ indicates the relative importance of a poster's likes or dislikes in comparison with his or her likes or dislikes towards video content ($0 \leqslant w(p_n) \leqslant 1$).

3.5. Level of intensity

Use of value- or attitude-related words along with the method of expressing strength can increase or decrease that strength. In this study, degree adverbs or other units expressing emotion (e.g., emoticons, exclamation marks, boldface type, etc.) were used to calculate found values or attitudes. Degree adverbs can be divided by grade. The first grade includes maximizers such as "considerably", "definitely", "badly", "substantially", and "incredibly"; the second one has boosters such as "so", "very", "really", "truly", and "surely"; the third one has compromisers such as "pretty" and "quite" and diminishers such as "a little", "a bit".

When users express their own values merely by using value-related words, the level of intensity is graded as 1, while the level of emotion increases or decreases according to the presence of degree adverbs. For example, suppose that a speaker used "useful" as a word with utility value and a strength of 1.0 point, and the degree adverb "a little", which decreases its strength ("a little useful"). This example would be calculated as having an emotional level of 0.5 points. As a result, the attitude level would be 0.5 (=1.0 × 0.5). In the same way, "very useful", in which the word "very" strengthens its value status, is graded as 1.6 points (=1.0 × 1.6), while "definitely useful" is graded as 2.0 points (=1.0 × 2.0) due to the use of "definitely".

3.6. Automated personality–sentiment–value analysis procedure

A sentiment analysis system measures sentiment polarity using four resources of the machine learning algorithm: set, domain knowledge, training corpus, and sentiment word list for the analysis of documents and texts (Cao et al., 2013). However, in this study, different architectures are used from those in the traditional sentiment analysis process in order to conduct deep sentiment analysis and to generate a PVA model by means of document information connected to the network through hyperlinks. Fig. 4 shows the system architecture based on the proposed sentiment value analysis procedure. The input of videos related to specific products produces a PVA model that is related to videos of those products. The PVA model contains the following information:

(1) Summary of user profiles (extracted from the characteristics of commenters);
(2) Value structure polarity (distribution and average intensity of three values);
(3) Attitude polarity (distribution and average of likes/dislikes);
(4) Causal relations between all characteristics in the user profile and all values within the value structure (R^2, etc.);
(5) Causal relations between all values within the value structure and attitude (R^2, etc.);
(6) Information about model validation (overall R^2, chi-squared value, degree of freedom).

The word refinement algorithm reads and tokenizes hyperlinked sets of documents on YouTube and then extracts

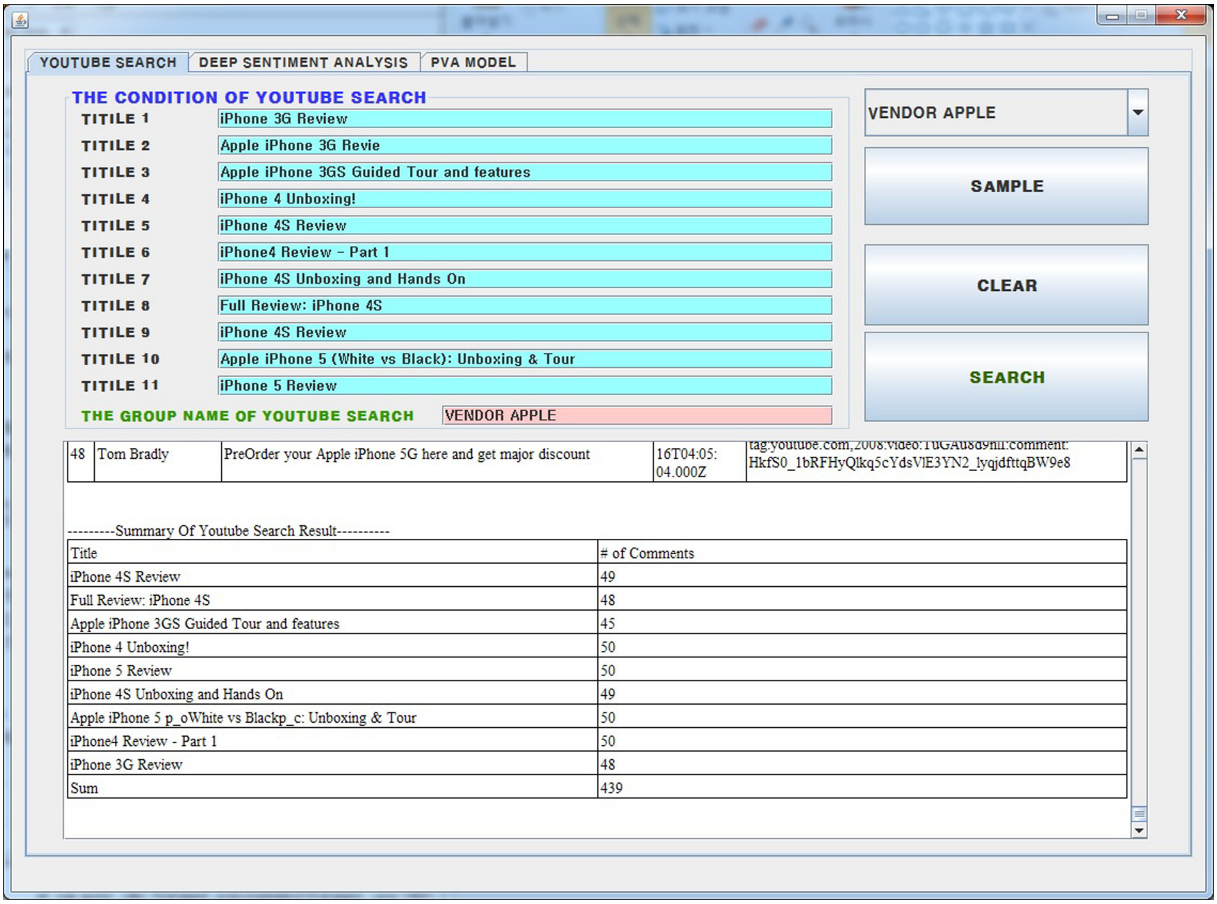


Fig. 7. Summary of collected videos and comments.

information on videos, commenters, and comments, as well as the time that the comments were made. Words that are seemingly associated with the analysis are also extracted in the form of a list see Fig. 5.

Model-based sentiment reasoning recognizes words that are associated with value structure, attitude, and intensity based on the word list described above. The model works to encode the data in a useful form to be input into an Euler graph database. For the purposes of encoding accuracy, users can extract a sentiment word list on the existing Euler graph offline and store it in a sentiment word repository in advance. Decisions as to the relation of these words to values and sentiments are based on value theory, psychological model-based information, and IT adoption theory. Values, attitudes, and user information as such are then encoded to NoSQL texts to be input into the Euler graph database and included in the Euler graph data model.

NoSQL is a generic term for a database management system that aims to enhance the scope and scale of data compared to existing relational data management systems. SQL was developed to solve a particular problem not addressed by existing systems: they lose their ability to process quickly as more and more data are stored. In this study, we saved data using an Euler graph with labels in nodes, which allows for insertion of properties and directivity.

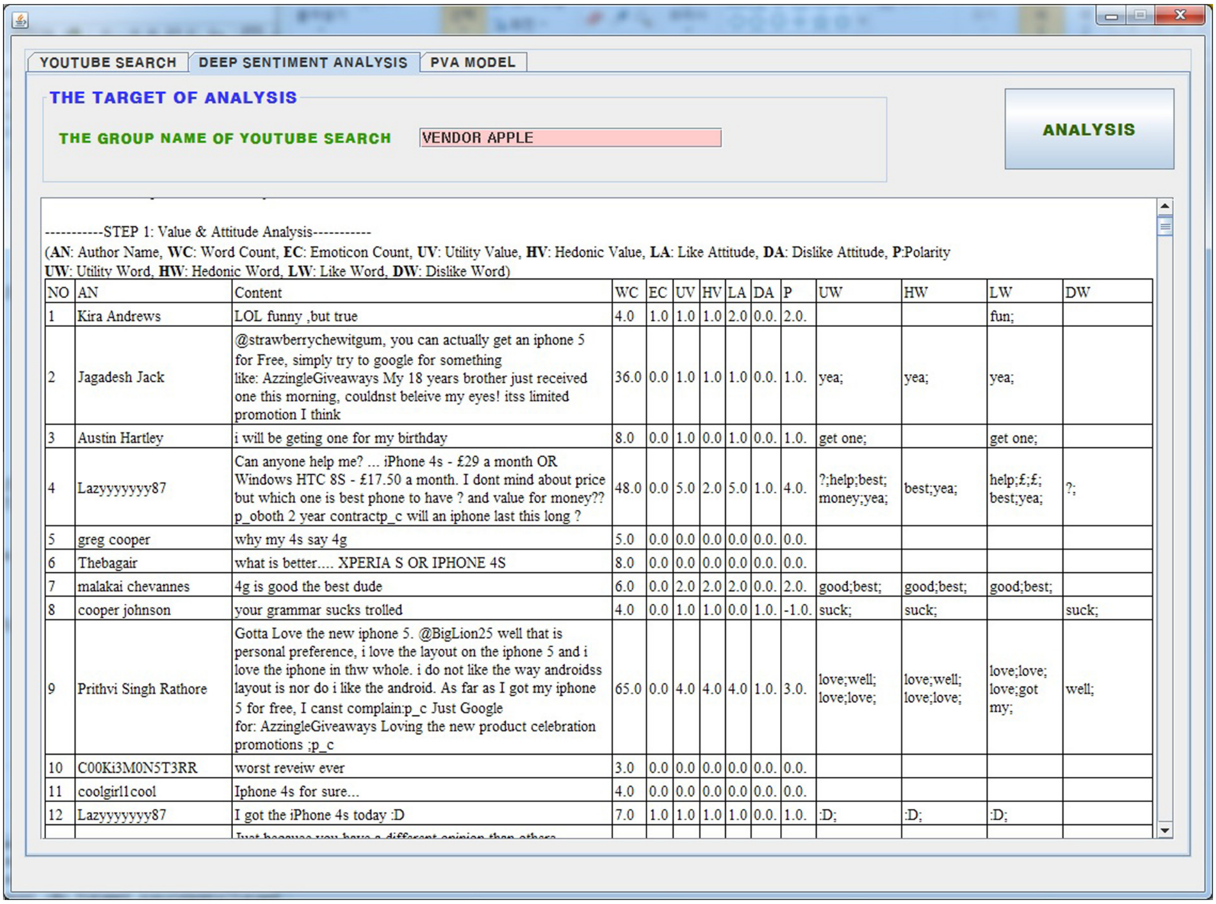
In the sentiment analysis, the value structure and attitude polarities are calculated based on data extracted from the Euler graph database, and values for profiles are identified. Finally, statistical analysis for these values is conducted using a PVA formulation algorithm to produce a PVA model.

4. Validation

4.1. Implementation

The system consists of three functions: gathering information on YouTube, the PVA model, and path analysis. To gather information on YouTube, we used the YouTube-related search tool Open API, which is provided by YouTube (Fig. 6). Next, for the PVA model, we used a dictionary of words related to personality, value structure, and attitude to conduct a frequency analysis on each comment (Fig. 8). In addition, information such as the number of words in a sentence and use of emoticons was obtained and included as each individual commenter's character information (profile). Lastly, a path analysis on the PVA model was conducted using a multiple regression method built on the character information and the outcome of the frequency analysis in the PVA model (Fig. 11). Path analysis allows measurement of the effects between the factors in the PVA model through path coefficients, enabling clear understanding of the value structures of the consumers for the products. Using this information from YouTube reviews, businesses are able to establish strategies to specialize and categorize products.

An implementation example is as follows. Fig. 6 displays a screen showing input of the details of the YouTube content and the outcome of its collection. YouTube content titles related to the product groups to be analyzed must be entered, as well as the name of the related product group. The group name is normally used for easy grouping of content to be analyzed while the PVA frequency and path analyses are conducted. The collected information



NO	AN	Content	WC	EC	UV	HV	LA	DA	P	UW	HW	LW	DW
1	Kira Andrews	LOL funny ,but true	4.0	1.0	1.0	1.0	2.0	0.0.	2.0.			fun;	
2	Jagadesh Jack	@strawberrychewitgum, you can actually get an iphone 5 for Free, simply try to google for something like: AzzingleGiveaways My 18 years brother just received one this morning, couldnst beleive my eyes! itss limited promotion I think	36.0	0.0	1.0	1.0	1.0	0.0.	1.0.	yea;	yea;	yea;	
3	Austin Hartley	i will be geting one for my birthday	8.0	0.0	1.0	0.0	1.0	0.0.	1.0.	get one;		get one;	
4	Lazyyyyyyy87	Can anyone help me? ... iPhone 4s - £29 a month OR Windows HTC 8S - £17.50 a month. I dont mind about price but which one is best phone to have ? and value for money?? p_oboth 2 year contractp_c will an iphone last this long ?	48.0	0.0	5.0	2.0	5.0	1.0.	4.0.	?;help;best; money;yea;	best;yea;	help;£;£; best;yea;	?;
5	greg cooper	why my 4s say 4g	5.0	0.0	0.0	0.0	0.0	0.0.	0.0.				
6	Thebagair	what is better.... XPERIA S OR IPHONE 4S	8.0	0.0	0.0	0.0	0.0	0.0.	0.0.				
7	malakai chevannes	4g is good the best dude	6.0	0.0	2.0	2.0	2.0	0.0.	2.0.	good;best;	good;best;	good;best;	
8	cooper johnson	your grammar sucks trolled	4.0	0.0	1.0	1.0	0.0	1.0.	-1.0.	suck;	suck;		suck;
9	Prithvi Singh Rathore	Gotta Love the new iphone 5. @BigLion25 well that is personal preference, i love the layout on the iphone 5 and i love the iphone in thw whole. i do not like the way androidss layout is nor do i like the android. As far as I got my iphone 5 for free, I canst complain:p_c Just Google for: AzzingleGiveaways Loving the new product celebration promotions ;p_c	65.0	0.0	4.0	4.0	4.0	1.0.	3.0.	love;well; love;love;	love;well; love;love;	love;love; love;got my;	well;
10	C00Ki3M0N5T3RR	worst reveiw ever	3.0	0.0	0.0	0.0	0.0	0.0.	0.0.				
11	coolgirl1cool	Iphone 4s for sure...	4.0	0.0	0.0	0.0	0.0	0.0.	0.0.				
12	Lazyyyyyyy87	I got the iPhone 4s today :D	7.0	1.0	1.0	1.0	1.0	0.0.	1.0.	:D;	:D;	:D;	

Fig. 8. Value and attitude analysis of each comment.

Table 2
Sample intensity words.

Word	Intensity	Note
!	1.2	Suffix
Really	1.5	Prefix
Badly	1.8	Prefix
Super	1.5	Prefix
Don't	−1	Prefix
Slightly	0.5	Prefix
A little	0.5	Prefix
A few	0.5	Prefix
Quite	1.2	Prefix
So	1.5	Prefix
Definitely	2	Prefix
Certainly	2	Prefix
A lot of	1.8	Prefix

is then confirmed by the output of each video's content in the form of a table, as shown in the lower screen in Fig. 6. A summary of the content of each video is provided in Fig. 7.

Fig. 8 shows the value/attitude analysis of YouTube comments by product group. We calculated the number of words and the number of emoticons used in each comment. We also calculated the utility value, hedonic value (emotion), number of likes, and number of dislikes based on the frequency analysis of value and attitude (Tables 2 and 3). Polarity value can be obtained by subtracting values for dislike from values for like. Data were also arranged to check the results of the analysis through the words.

Table 2 shows the classification of words used in actual comments, including conceptual words from previous study models related to sentiment words. In total, 197 sentiment words were developed for the analysis.

Fig. 9 provides statistical information such as frequency, standard deviation, and average for each factor in the PVA model.

Fig. 10 displays the screen after the path analysis using the results of the sentiment classification. Path analysis is used in statistical analysis of causal relationships between constructs. The results show significance levels, and the path coefficients show the levels of impact between constructs.

For the path analysis, we first divided the model into three types for the regression analysis, as shown in Fig. 11. In the figure, WC, EC, UV, HV, and P indicate the number of words in a review, the number of emoticons in a review, the utility value, the hedonic value, and attitude polarity, respectively. Next, a test was conducted of the model's significance using multiple regression analysis. An R^2 value was calculated related to the goodness-of-fit of the model, and ANOVA was used to determine p-values related to the significance of the model. We also calculated a beta value for each independent variable and constant term. Lastly, a path coefficient was calculated as a coefficient value drawn from the model.

Fig. 12 shows the calculated path coefficients and goodness-of-fit of the regression model, as indicated by the numbers, while significance values are marked with asterisks (*). Two values are <0.01, and one is <0.05.

4.2. Performance evaluation

For a performance test of the method proposed in this study, an Euler graph was used to evaluate IT product advertisement videos, comments related to them on YouTube, and data on other videos posted by the commenters. We developed a Java application to

Table 3
Performance comparison.

Sentiment analysis method	Media/information richness				Agility
	Sentiment classification	Sentiment polarity	Depth of analysis	Channel abundance	Agility of analysis
Pointwise mutual information Turney & Littman (2003)	O		One dimensional (fact-opinion)	Low	
Semantic Orientation Wang and Araki (2007)	O	O	One dimensional	Low	
Artificial intelligence approach Read (2005)	O		One dimensional	Low	Low
Semantic-based approach Kumar (2011)	O	O	One dimensional	Low	High
Proposed method	O	O	Two dimensional (fact-opinion/ cause-effect)	High (PVA model, diagram)	High

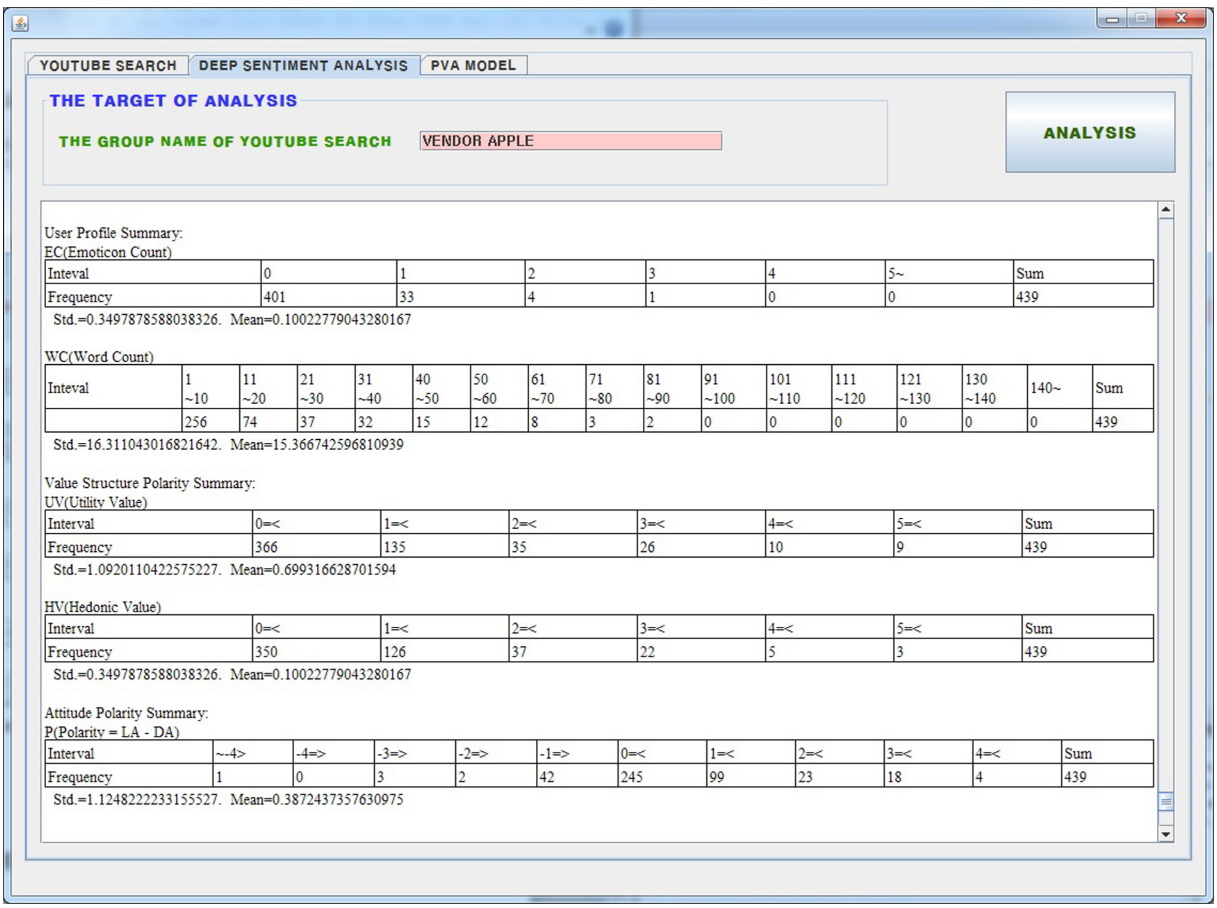


Fig. 9. Value-attitude analysis (standard deviations, average values, and frequency).

collect this information, which was run on an IBM PC with internet access. For efficiency, the network included more than 100 nodes and 10 types of smartphone advertisement images. Node information was administered by Neo4j, which was converted to a spreadsheet for easier analysis.

The dataset consisted of 2670 reviews of 65 YouTube multimedia for smartphones made by 12 companies such as Apple, Samsung, and LG. Approximately half of the reviews were positive (50.9%) and the rest were negative (49.1%). The criteria for selection of multimedia in the experiment were based on the number of reviews. Information on comments was administered by Neo4j, which was converted to a spreadsheet for easier analysis.

Primary information obtained from the comments included product vendor, model name, YouTube multimedia title, author's name, and the actual text in the comment. Secondary information was obtained following recognition of utility value polarity, hedonic value polarity, attitude polarity, and level of intensity. It included the number of words used in a review, the number of emoticons used in a review, the hedonic value, and the utility value.

The model was generated though the PVA model formulator included in the prototype system.

Information richness is an underlying concept frequently used to build up performance measures such as key value frequency, attitude polarity, value structure polarity, and the PVA model. Media/information richness theory states that media differ in their ability to carry varied types of information (Rice, 1993). Media classifications as suggested by this theory include face-to-face

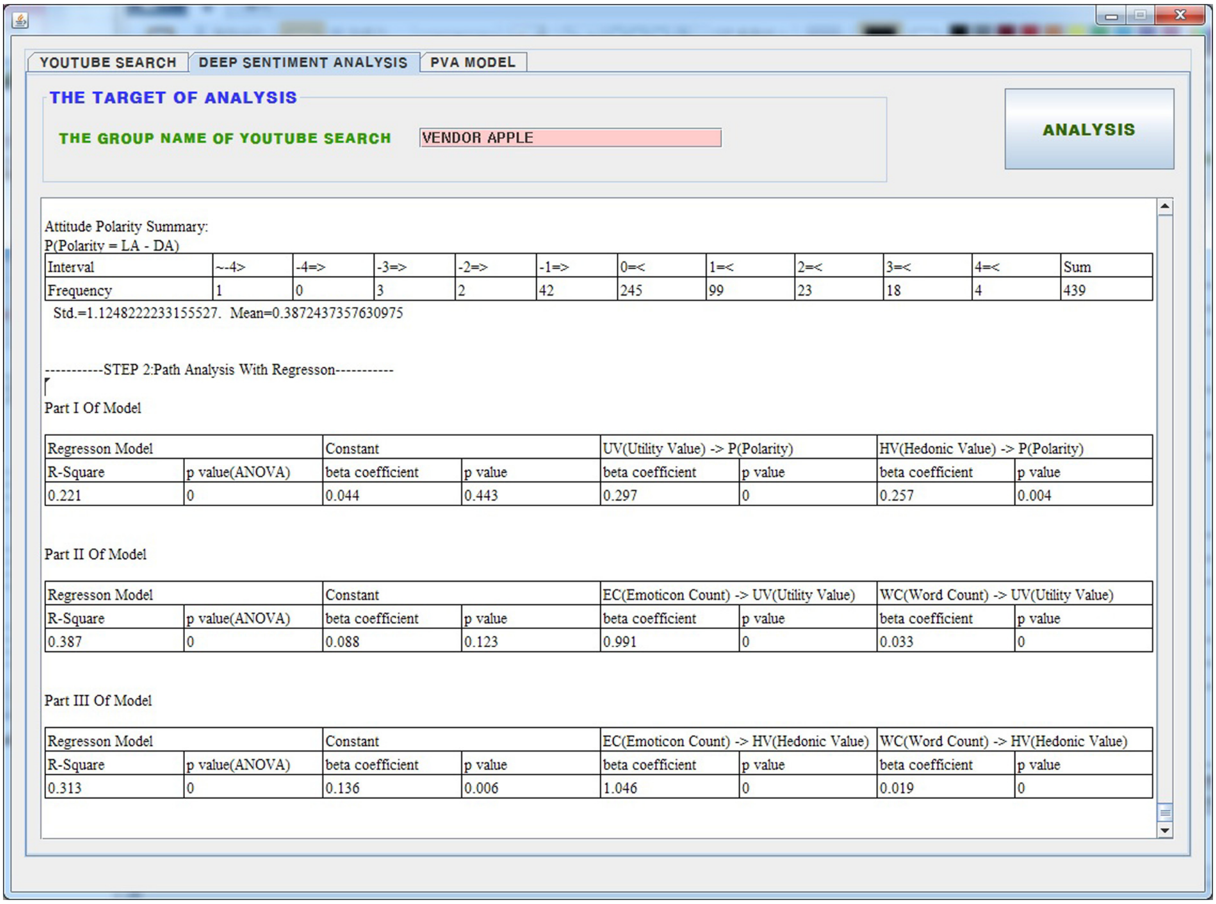


Fig. 10. Path analysis with multiple regression.

communication (the richest), telephone, written and addressed documents (such as letters, notes, and memos), and unaddressed documents such as fliers and newsletters (the poorest) (Daft, Lengel, & Trevino, 1987).

The performance measures consisted of media/information richness and agility of analysis. For media/information richness, sentiment classification simply classifies an opinionated document as expressing a positive, negative, or neutral opinion (Das & Chen, 2007; Kennedy & Inkpen, 2006). It shows only whether a sentence or word is positive, neutral, or negative, regardless of its intensity. When a method presents the degree of sentiment, it can address sentiment polarity. The scale can be represented as an integer (3, 5, or 7) or as a real number. Depth of analysis indicates if the method only shows the result of sentiment analysis or provides additional information on top of the analysis results (i.e., what affects the result, or the causality between the determining variable and sentiment polarity). Information obtained from social media can be broadly categorized into two dimensions: facts/opinions and cause/effect. Facts are objective expressions about entities, events, and their attributes; opinions are subjective, including people's cognition, feelings, or attitudes. Among these, subjectivity classification (as distinct from sentiment classification) has been extensively studied in the text mining community (Liu, 2010). Causes refer to the conditions or determinants associated with effects or results. Channel abundance designates the diverse means of displaying sentiment analysis results: numerical data only, text, diagrams, models, and so on.

Using these performance measures, the evaluation was performed. Table 3 shows the results. Four baseline approaches are included for comparison of performance: pointwise mutual information, semantic orientation, artificial intelligence, and the semantic-based approach. Turney and Littman (2003) used seven positive and seven negative words as seeds, and determined semantic polarity according to the pointwise mutual information-information retrieval method. Wang and Araki (2007) applied the semantic orientation-pointwise mutual information algorithm for mining opinions and sentiment in weblogs. We balanced factorial and neutral expression detection methods and achieved a well-balanced result. Read (2005) used an artificial intelligence approach for predicting the sentiment of an article using a data set of emoticons. The emoticon-trained classifiers performed well on longer articles, but were ineffective on movie data sets and newswire articles. Kumar (2011) proposed a semantic-based approach to capture users' opinions. Their sentiment product lexicon involved use of adjectives to identify sentiment polarity. Their approach was more efficient than the conventional artificial intelligence approach (e.g., support vector machine), which involves training and testing phases to identify sentiment classification rules. They considered multimodal opinion elements like normal phrases, emoticons, and short words popularly expressed by users in documents.

Although several problems emerged when the YouTube data were treated in the form of an Euler graph, we found that a schema expansion fit well with a diverse range of YouTube pages (e.g., video page, comment page, video list page provided by the same person). Schema expansion can be reflected at the time of node definition. The model showed excellent expression of unstructured information. In particular, it allowed proper management of extremely unstructured information in the form of videos or comments. Storage of the unstructured information was made possible

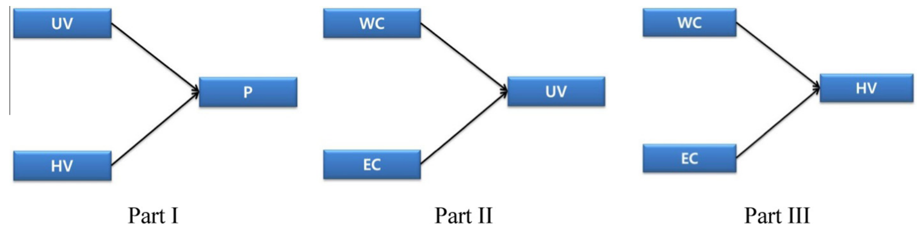


Fig. 11. Path analysis model.

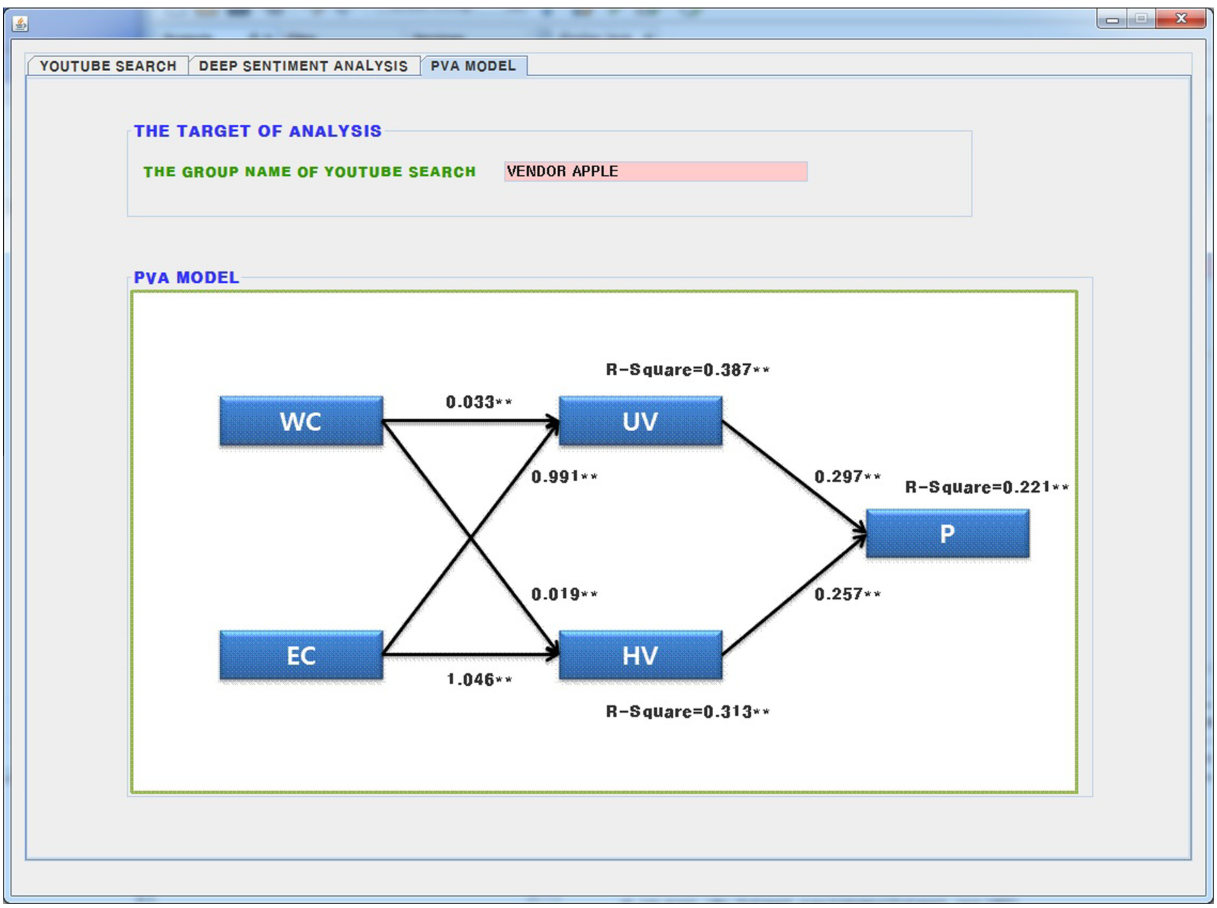


Fig. 12. PVA model based on path analysis with multiple regression.

by treating videos and comment content as a Rowkey of nodes and defining related information as attributes of nodes. An additional advantage was its good scalability. Generally, a join operation is needed with existing relational data models for horizontal expansion among videos, users, and comments; however, this model allowed easy connection in NoSQL, which simply treats high-capacity unstructured data as one of the nodes instead of as a join operation at the simulation stage. This feature did not increase the amount of time necessary for acquisition of relevant information, despite the increase in the number nodes. Lastly, the graph-based NoSQL expressed the data better than other NoSQL types. Graphs are an easily understood method of visualization of information. Several commercial tools for the same purpose use graphic methods (Amar & Stasko, 2005). In terms of mathematics, graphs represent more information than a tree structure or lattice networks. An Euler graph, which can show all labels, attributes, and directionalities, has even more expressive abilities than other graphic methods.

5. Conclusion

Thousands of people and companies use social media as a way to share their thoughts with others. Videos are particularly popular and useful tools for sharing unstructured knowledge. A very diverse range of knowledge is produced, managed, and expanded in video form. A video-sharing service such as YouTube can therefore be a very successful marketing tool. Moreover, reviews by potential customers of products they view in videos provide important raw material that represent customers' actual voices. From these reviews, companies can gain information about users' attitudes towards products and about their values. Thus, many businesses, professionals, and individuals post their product-related videos on YouTube for advertisement purposes.

The deep sentiment analysis method proposed in this paper contributes to the sentiment analysis research and its application to marketing. First, the method allows extraction of reviewers' attitudes, which have more meaning than sentiments or likes and dislikes. Rather than unstructured data about sentiment classification and sentiment polarity, this method identifies attitudes, which have been regarded as more direct and significant psychological constructs than just emotions by academic researchers in psychology and business. Second, the method allows extraction of a two-dimensional structure of value (utility and hedonic values) as determinants of reviewers' attitudes towards the product shown on YouTube. Previous sentiment analyses fail to explain degrees of likes or dislikes, or to determine causality in terms of correlations and coefficient values. Finally, the proposed method intentionally avoids gathering information about personal traits or personality from the reviewers' profiles, which appear in the annotations about the reviewer's profile in the YouTube service, in order to avoid privacy issues. Instead, the method identifies the reviewer's traits in the review text using constructs such as word count and usage of emoticons. Thus, the deep sentiment analysis method along with newly developed sentiment analysis tools presented here may improve the quality of marketing decision-making by allowing market segmentation and identifying the voice of customers from big data residing in social media such as YouTube.

This study also demonstrated the value of YouTube as an unstructured knowledge management tool. Based on materials revealed in unit video pages on YouTube, we suggested a method of acquiring information about specific value structures and attitudes related to IT products. Value structures in particular comprised four factors on two dimensions: utility and hedonism, which included most factors influencing IT use intention, as addressed in recent information systems theories. Using the proposed method, we were able to measure the intensity of the value structures of certain commenters by conducting a textual analysis of comments using a parser. This method offers richer information compared with current sentiment analysis tools, which simply provide facts about sentiment polarity and some corresponding information.

Future studies may determine how to prove the efficacy of the proposed method and its usefulness to decision-makers. The graphic user interface needs to be improved for usability and acceptance of the deep sentiment analysis tool. Second, the robustness of the proposed method must be demonstrated in terms of scalability; benchmark data volume must be large enough to be regarded as a big data set. In addition, an exhaustive search of marketing and management information system research models that include value-related constructs must be used to improve the proposed method. This enhancement will increase user satisfaction with this tool and willingness to adopt it.

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