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What content and context factors lead to selection of a video clip? The heuristic route perspective

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Abstract
The popularity of watching video clips on mobile devices is rapidly increasing. The providers of such video services have developed mobile capabilities and have worked to increase their video selections. This study investigates the effect of the factors of preview content (the thumbnail and the title) and context (the popularity cue and the serial position) on video selection in a mobile context by adopting dual process theory and the model of attention capture and transfer. We performed a logit transformation on the dependent variable, and then applied generalized least squares (GLS) regression to analyze 206,221 logs and 323 thumbnails and titles of a video service. Image and text- mining techniques were used to ascertain the level of valence and response to content. This study has four main findings: (1) low valence but high arousal of a thumbnail has a positive effect on video selection; (2) high valence and arousal by a title has a positive effect on video selection; (3) the upper serial position of a video clip and a high popularity cue have a positive effect on the video selection; and (4) the length and recency of a video have a positive effect on the video selection. The results of this study suggest practical implications to help the programming and marketing strategy of the video service as well.

Keywords Mobile context · Video clip · Sentiment analysis · Heuristic route · Order effect · Bandwagon effect · Machine learning · Text mining

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1 Introduction

Short-form content optimized for the mobile environment is increasingly popular. In particular, the viewing of short videos ("video clips") is skyrocketing every year and accounts for 60% of use on various mobile devices [1]. The growing market for video clips is centered on YouTube, the most popular mobile video service. The video ad revenue of YouTube is expected to reach approximately $2.89 billion in 2018 [2]. Numerous other mobile video services have also been established. Broadcasters, such as NBC, and platform companies, such as Youku in China and NAVER TV and GOM TV in Korea, also provide videos through their mobile webs and apps. They deliver various types of video clips such as user-generated content, music videos, and TV highlights.

With the increasing number and variety of video clips, recommending user favorites on the front page (i.e., the trending page in YouTube) has become more important to video services. Due to the display of video clips on the front page, recommendations as determined by the service's algorithms have a significant effect on users' viewing behavior [3]. Recommending popular video clips on the front page increases not only service satisfaction but also the number of plays and, therefore, advertising revenue [4]. Recommendations on the front page are significantly more important in the mobile environment than in the PC environment for two reasons. First, fewer video clips can be recommended on the typically smaller mobile front screen than on a PC; for example, the mobile device may only display one or two videos in a row on the front page compared with five or more on a PC [5]. The second reason is that information previews, such as thumbnails and titles, account for a larger portion of the service screen [6]. Due to the changing mobile environment, providers of video services face challenges in their efforts to increase the selection of videos available to users as part of an ongoing effort to increase revenue.

However, even within the context of current circumstances, few studies have examined the factors that affect mobile users' video selections. Because mobile services without thumbnails or titles are so few, it has become more important to study the effectiveness of video previews rather than the presence of preview content. Recent studies have begun content classification [7] or content analysis [8]. Besides, the context factors affecting users' video selection have also changed because of device differences [5]. Nevertheless, we found a lack of theoretically and empirically validated explanations of video selection in the mobile environment.

Thus, this study seeks to determine the role of factors that affect video selection in the mobile context. This lack of knowledge leads to our research question: *What content and context factors drive video selection on the front page of a mobile video service?* To address this question, this study develops and empirically tests the content and context factors that affect video selection in the mobile service context. According to dual process theory [9], information processing proceeds on a heuristic route when individuals have a low level of involvement. Video services usually have a low selection cost and high uncertainty value concerning content [10]. Hence, a user's information processing tends to proceed heuristically [11, 12]. Environmental cues that work with less effort in the decision-making process cause heuristics [10]. To the best of our knowledge, this study is the first to empirically investigate which context and content factors affect video selection on mobile devices.

In this study, thumbnails and front page titles of recommended video clips were obtained from a video service in South Korea. We applied data mining technology to the preview content to conduct a sentiment analysis of the overall content. In addition, we obtained user log data, content-related serial positions, and popularity cue data. Our results can help produce guides to develop preview content and recommend a strategy for video service providers. We expect to find content and context factors that affect video selection and, thereby, increase consumption and revenue. In the following sections, we provide a theoretical background and literature review. We then discuss the development of hypotheses based on the theoretical framework. Next, we introduce the research methodology and report the test results. Based on the discussion of the findings, we address the implications for research and practice.

2 Conceptual background

2.1 Dual process theory

Understanding people's information processing, which usually precedes making decisions and taking action [13], should help us explore the factors that affect video selection. Therefore, to explain the information processing involved in selecting a video, this study selects the dual process theory as its theoretical foundation.

This theory holds that systematic processing or heuristic processing—a determination governed by the degree of involvement or selection cost—determines a user's choices [9]. If the degree of involvement and the selection cost are high, then systematic processing is invoked to examine the information or message carefully. If the opposite is true, then the source or environment resorts to heuristic processing [13]. Selection cost and personal involvement are generally low because most video services offer free videos [10, 12]. Therefore, in the mobile video context, users' information processing proceeds mostly heuristically [11, 12]. In practice, if a user has a specific purpose (e.g., if there is a specific video he or she wants to watch), then system processing would govern. However, in such a case, selection usually occurs through a search of keywords for the specific video or going to one's own subscription channel list [14] rather than selecting a video from the front page. Therefore, this study uses the perspective of the heuristic route in focusing on finding those factors that affect what users select from the front page of mobile video services. In this heuristic framework, environmental cues such as content and context factors determine video selection [15].

2.2 Literature review on content and context factors

The influence of content and context factors on user behavior has been examined recently in various fields. First, the previous studies have investigated the effects of preview content on users' decision making. For video services, video selection in the environment of desktop computers is affected by the presence of thumbnails and titles [12]. Researchers have also found that preview content influences user behavior in mobile e-mails [6] and print ads [16].

Second, extant studies have discussed context factors that influence user behavior based on the context effect. Research on the social network service (SNS) brand page found that posts with a higher position receive more customer engagement. A review site study also empirically found that the order of a review affects the review helpfulness from users [17]. Research on PC based the music community [18] and the video service [10] also found that popularity cues (e.g., view count) influence content selection. However, content selection in the mobile environment differs from the PC environment: the importance of preview content has increased and the context factors that affect content selection have changed, thus requiring a re-examination of this phenomenon.

Table 1 summarizes the results reported in the previous studies. In the following subsections, we provide a concise review of the literature on content (i.e., preview content of a video clip) and context (i.e., mobile context) factors to explain the context of our study and identify research gaps.

2.2.1 Preview content of a video clip

Content selection is influenced by how the preview content was produced [6]. Preview content on a video service includes a thumbnail, which is a "snapshot" image from the video, and a title, which is a text sentence that describes the video. Previous studies have focused on whether such content was present and not on which preview content influences the selection of a video by a potential viewer [6, 12, 16]. Therefore, we need to analyze the effect of the elements of preview content on a potential viewer's selection decision. We applied the model of attention capture and transfer [16] as the theoretical background for an examination of this preview content.

The model of attention capture and transfer is a theory to explain the attentional mechanisms of specific content [16]. This model contends that two processes lead to selective attention: a top–down (or goal-oriented) mechanism and a bottom–up (or stimulus-driven) mechanism [19]. Attention originates through the top–down mechanism because of personal interest or reasons. For example, on video services, a user is stimulated to either select a video or search for specific content [4]. Conversely, attention is captured in the bottom–up mechanism by the content elements. In this mechanism, the user automatically responds to images or text elements. For example, the results of eye-tracking procedures for 110 print ads have shown consumer attention toward image and text elements [20].

When a user purposelessly selects content from a video service's front or trending page, the elements of the content stimulate his or her attention and its subsequent selection—an example of the bottom–up mechanism. Content elements such as image and text that may affect attention are size, shape [16], and emotional stimulation [21, 22]. Neuroscience research has found by event-related potential analysis that for reasons of survival, humans are more focused on emotional images and text in terms of natural selective attention [23–25]. This suggests that the perceptual encoding of image and text are under the command of the approach-avoidance

Table 1 Summary of previous research

Factors of concern		Research	Context	Findings
Content factors		Fu [12]	Video service	The presence of preview contents increased user selection of the video. In other words, the increase in video views empirically explains the impact of the presence of a thumbnail and title
		Weaver et al. [6]	Mobile e-mail	Using a number of preview lines in an e-mail increases user activity (e.g., scrolling distance and the number of scroll actions) more than not providing any preview, especially in the mobile context
		Pieters and Wedel [16]	Print ad	The ad elements (e.g., pictorial and text) each have a significant impact on the user's advertising attention in the print ad context
Context factors	Serial position	De Vries et al. [7]	SNS brand page	Due to the primacy effect, which is one of the order effects, the higher the post ranking, the higher the customer engagement
		Zhou and Guo [17]	Restaurant review site	A higher-order review affects the number of "useful" votes a review receives. That means the order of a review affects the review helpfulness from users
	Popularity cue	Dewan et al. [18]	Music Community	The popularity (e.g., favorite and sales rank of a song) affects music selection (i.e., listening count) in an online music community
		Fu and Sim [10]	Video service	A video showing higher view counts attracts more users than one showing lower view counts. Thus, the bandwagon effect is significant in the video service context

motivational system [24]. In other words, users autonomously focus their attention and select preview content that generates an emotional feeling. This study thus focuses on the emotional stimulation of preview content.

Two aspects of emotional stimulation, valence and arousal, take key roles in human behavior and decision making studies [23, 26, 27]. Russell proposed a method for numerically measuring emotion stimulation by a two-dimensional space. Russell's circumplex model reveals that valence and arousal are present in other two-dimensional spaces [28]. Thus, it is essential to examine valence and arousal of content about the condition of attentional preview content. Prior research has shown that attentional preview content affects user satisfaction and selection [6]. Video service providers especially care about preview content that stands out among many videos to capture the attention of users [29]. For this reason, demand has increasingly grown for a production guide for creating effective attentional mobile preview content [30].

2.2.2 Mobile context

Many decisions are based on the current environment and not on the preference system [31]. This phenomenon could be explained as a context effect. The context effect refers to the tendency for selection decisions to change according to a user's specific situation or context [31]. A user's decision making can especially be influenced by the order in which items for selection are arranged [17] and by social or peer influence [10]. The effect of the order of items has emerged as an important research topic in persuasion communication and psychology [32]. The order effect is a phenomenon in which a user's response varies according to the order in which information is presented [33]. The observation that information initially presented is more persuasive is called the "primacy effect," and when information presented later is more persuasive, it is called the "recency effect" [32]. These effects differ according to the degree of search cost or personal involvement. The primacy effect appears for high search cost and a familiar subject, whereas the recency effect appears for the opposite case [32]. In content services, people generally start browsing from the initial items to reduce the search cost; thus, the primacy effect affects a user's actual behavior [5]. Thus, we expect that the order effect will be significant in the mobile environment.

As for social and peer influence, numerous studies have documented the bandwagon effect [10, 34]. The bandwagon effect refers to the phenomenon that information that is popular with the public affects individual selection [34]. It is a concept similar to herd behavior [35], which describes behavior that is influenced by the decision of the peer group [35]. The bandwagon effect and herd behavior occur because popularity provides better cognitive value to the subject [35]. This behavior can be seen in various fields, such as blockbuster movies, fashion trends, and digital music rankings [36]. In online content services, users are also affected by popularity cues (e.g., views, hits, downloads, likes) to reduce the search cost and cognitive load [10, 18]. Video services use popularity cues such as *View counts* and *Like counts,* which, respectively, indicate how many users have seen and reacted positively to a video [37]. However, few studies have examined how each popularity cue affects decision making differently, especially in a mobile context.

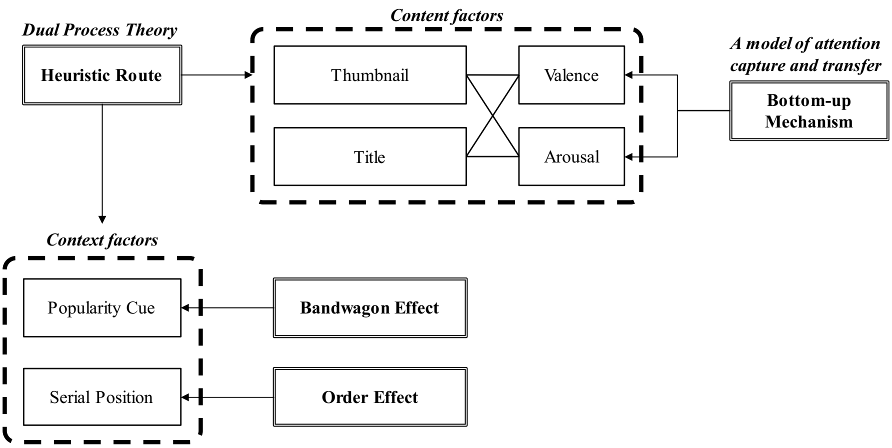

Fig. 1 Theoretical framework

3 Theoretical framework and hypotheses

3.1 Theoretical framework

When low selection cost and personal involvement occur together, such as on the front page of mobile video services, a user's information processing operates heuristically [11]. According to the dual process theory, heuristic processing is affected by environmental cues such as content and context factors [12]. The thumbnail and title are the content factors of a mobile video service, and the context factors are the serial position and popularity cue. To analyze in detail which elements of the thumbnail and the title generate an effect, we adopted the model of attention capture and transfer [16].

The purpose of this study is to investigate what factors influence a user's selection of a video from among those recommended on the mobile front page. In this case, because stimuli influence video selection, we used the bottom–up mechanism for the theoretical framework. According to this mechanism [16] and Russell's circumplex model [28], this study proposes valence and arousal as elements of the thumbnail and title. The context factors are the serial position and popularity cue based on the order [33] and bandwagon effects [34]. Figure 1 shows the proposed theoretical framework, combining dual process theory [9], content and context factors, and the model of attention capture and transfer [16].

3.2 Content factors

Content elements determine a user's perception and attention according to the bottom–up mechanism [16]. Representative content elements include distinctive size, shape, and emotional stimulation. However, two elements (size and shape of each preview content element) of the more than 10 video clips on a mobile front page are the same [6]. Thus, we argue that the emotional stimulation of the preview content will affect a user's attention and his or her selection of a video clip in the context of a mobile video service. Specifically, based on Russell's circumplex model, we focus on the valence and arousal of preview content.

Under normal circumstances, positive content generates a positive feeling and affects human behavior positively [8, 21, 22]. Ang and Low argue that positive ads evoke a cognitive elaboration under the same conditions [21]. In online services, the positive emotion of content can be easily translated into action. For example, the more positive the online content, the more likely it is to lead to action [22].

Preview content on mobile video services comprises a thumbnail as an image and a title as text. Images catch a user's attention and then quickly lead to behaviors with less effort [16, 26]. Thus, the user perceives positive thumbnails as images more clearly than other factors, which draws on the bottom–up mechanism [16]. Therefore, we propose the following hypothesis.

H1 A high level of thumbnail (image) valence has a positive effect on video selection.

As another element of preview context, the valence of the title of a video clip may affect users' attention and behavior similarly. Previous research found that the positive valence of a text influences readers' attention, decision making, and concentration processes [16, 38]. Neuroscience results also have shown that positive text evokes human attention and action [26]. For example, a positive peer review influences people's decision making [27]. As the valence of a video clip title is more positive, the video will attract more attention from the service user and leads to those users' video-clip selection behavior from the perspective of the bottom–up mechanism [16]. Therefore, we propose the following hypothesis.

H2 Ahigh level of title (text) valence has a positive effect on video selection.

In addition to valence, arousal serves as an emotional stimulation according to the circumplex model [28]. Arousal by content attracts a reader's attention from the perspective of the bottom–up mechanism [16]. Content that generates a high level of arousal not only attracts users but also leads to positive customer behavior [39]. Specifically, a high degree of arousal from images generates users' attention and influences users' action regardless of positive or negative feeling [22]. With images as a content factor of a video clip, this arousal can occur in response to a sexual [40] or sensational scene that can also be used in thumbnail production. Therefore, we propose the following hypothesis.

H3 A high level of thumbnail (image) arousal has a positive effect on video selection.

The title of a video clip is another content factor that can produce arousal. Text-generated arousal can initiate users' attention and selection from the perspective of the bottom–up mechanism [16]. The title text is mainly influenced by word units [26, 41]. For example, words such as "kiss," "sexy," "betray," "fire," and "murder" generate a relatively high arousal response [41]. The morpheme has been verified for nouns and adjectives. The common conclusion of preview studies is that text arousal attracts high attention and influences users' decisions [23, 26, 27]. In other words, the higher the degree of arousal generated by the video title, the more positive the effect on video selection. Therefore, we propose the following hypothesis.

H4 Ahigh level of title (text) arousal has a positive effect on video selection.

3.3 Context factors

The order effect is present in the process of video selection in a mobile context. From the perspective of the primacy effect [32], there is a high probability of selection of the items at the top of a list [17] because selecting items at the top reduces the time spent searching for information. Economically, if the marginal search cost is higher than the marginal profit, people select the first items without searching [42] because it reduces the cognitive uncertainty of selection [43]. With online services, because there is high uncertainty in content selection and low selection cost, there is a high possibility that the primacy effect occurs. In e-commerce, it has been proven empirically that vendors at the top of a list have a higher positive effect on vendor acceptance [44].

Similarly, the upper serial position of online reviews was more helpful to users than a lower serial position of online reviews [17]. On SNS brand pages, the upper serial position of posts receives the most likes and comments [7]. It has an especially strong order effect in a mobile environment because the navigation cost there is higher than for a PC [6]. Thus, the primacy effect related to the serial position of a video would occur in the selection of a video clip.

H5 The upper serial position of a video has a positive effect on video selection.

The bandwagon effect [34] can also occur on a video service as users select videos with high popularity indicators such as the numbers of views and likes. Online popularity indicators reduce content uncertainty [10]. Through heuristic processing [9], high numbers of views and sales volume information help a user choose easily with the expectation that the item has a high value. This effect also occurs in social networking services (SNS) and in e-commerce in which value uncertainty is high [11]. For example, in the online music community, it has been revealed by objective data from the famous music community Hype Machine that listening to music by users is strongly related to the popularity of each song [18]. On the same principle, it can be expected that information such as a high number of views and likes on a video service will positively influence video selection. Previous research has found that when there is high online viewership, these popular videos are preferred over other videos, so there is a high possibility that views will also increase in the future [10, 12, 14, 45]. Thus, the bandwagon effect related to the popularity of a video would occur in the selection of a video clip.

H6 The high popularity of a video has a positive effect on video selection.

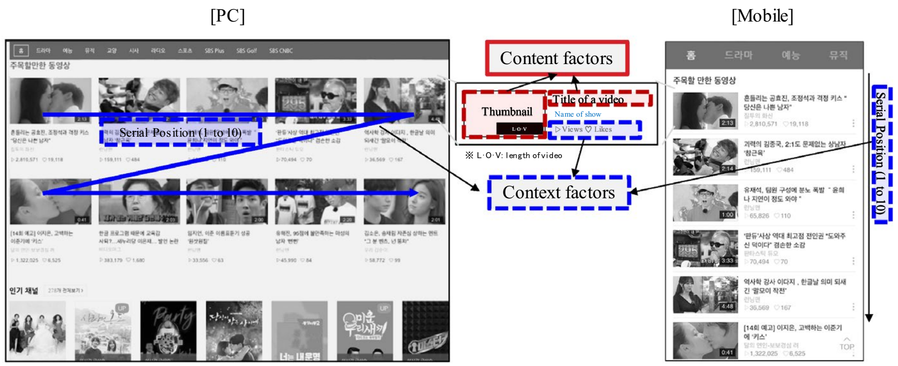

Fig. 2 Screenshot of the S-Service front page

4 Research methodology

4.1 Research context

We collected data from S-Service,[1] which is the largest video service provider in Korea. Most of S-Service's videos are professional videos provided by content providers such as studios and broadcasters. S-Service provides its content providers with a brand page, such as a YouTube channel, and provides a content management system to upload videos and programming videos on the front page.

On S-Service, content providers recommend videos by using an S-Service recommendation algorithm. The front page displays a list of 10 recommended videos. Users can review videos along the recommendation list across pages. Recommended videos are ranked from 1 to 10, and the recommendations include the thumbnail, title, numbers of views and likes, and video length (see Fig. 2). The video recommendations of S-Service change daily at about 9 a.m. The user interface of S-Service is similar to global video services such as YouTube, NBC, and Youku. S-Service also distributes advertising revenue to the content providers, similar to the YouTube system.

The general procedure for watching the video in S-Service is as follows. S-Service recommends 10 videos (set with thumbnails and titles) on the front page. When the user clicks on one video, it is linked to the video details page (corresponding to the *Selection* variable in this study). The video is automatically played when linked to the video detail page in the PC environment. While, in the mobile environment, the user must press the play button to play the video.[2] In S-Service, the view count increases when the video is played more than 0 s (corresponding to the *View Count* variable in this study). There are a variety of ways to access video details pages,

[1] For reasons of confidentiality, we will refer to this Korean video service by the pseudonym "S-Service".
[2] S-Service has restricted auto play on mobile to prevent excessive cellular data charges. The user can change to setting for auto play on the preferences page.

including search, subscription channels, referral page, share, as well as the front page. The view count increases even if the video is played in these ways. That is, the number of clicks on the video and the video view count are different.

S-Service users can subscribe to their favorite brands and receive notifications when new video clips are uploaded. Users can connect to the front page of the brand and select among the ten recommended videos or select different videos by searching subpages. If they like the selected video, then they can click the "Like" button. The number of views is counted when the video starts. Although S-Service provides for PC Web, Mobile App, and Mobile Web services, the user interface (UI) of S-Service is different on mobile devices from on a PC. Mobile devices have a 1×10 matrix structure of video lists, whereas PCs have a 5×2 matrix; however, the recommended items, preview content, and other UI components are the same. S-Service's mobile play rate is about 63% and the PC play rate is 37%. In other words, people watching videos on mobile devices outnumber those on PC by almost two-to-one. In this study, 206,221 logs and 323 thumbnails and titles for 40 days of one brand page of S-Service were received and analyzed. The S-Service reviewed the overall data quality and provided reliable Unique User Identifier data from device information.

4.2 Data collection

4.2.1 Thumbnail elements: image sentiment analysis

We coded two major variables, valence and arousal of an image, using image sentiment analysis software based on machine learning tools (Complura [46] and IBM Watson) for each video's thumbnail (image). The Complura System applied visual sentiment ontology consisting of more than 15,630 adjective–noun pairs (ANP) [46, 47] and constructed a dataset by inputting *tags* and *meta-data* for over seven million images. Each image was trained to emotion and sentiment scores [46]. When uploading an image to the Complura System, the ANP was applied through a visual-based classification of the images and a sentiment score ranging from 1 (negative) to 5 (positive) was provided.

Next, an image's degree of arousal was obtained through IBM Watson. IBM Watson has become a representative system for analyzing big data with deep learning technology and is used by 20 industries in 45 countries and by over 80,000 developers. It also has over 500 partners and offers courses at 200 universities.[3] Visual analysis is one of its deep learning technologies. When images are trained through IBM Watson, it calculates a similarity rate between the image object and the learned image. We used Open Affective Standardized Image Set (OASIS)-based image data for IBM Watson to learn arousal image discrimination. OASIS gathered 822 participants from eight races through Amazon's Mechanical Turk (MTurk) to investigate the valence and arousal scores of images.

[3] IBM Watson developers' site. Retrieved July 23, 2017 from https://www.ibm.com/watson/kr-ko/what-is-watson.html.

For a variety of images, such as animals, objects, and people, the obtained image ratings are in circumplex space, with valence (measured on a 1–7 Likert scale) on the *x*-axis and arousal (also measured on a 1–7 Likert scale) on the *y*-axis. The sets of OASIS images allow their free use in research because they are not subject to copyright restrictions that apply to the International Affective Picture System (IAPS) [48]. Using the arousal score of the OASIS image set, we conducted data training by using the IBM Watson application programming interface (API). After the images used in the study were uploaded, Watson issued probability scores for whether the images generated arousal. In this study, 50% was applied as a threshold, with more than 50% coded as 1 (arousal image) and otherwise 0.

We have also conducted additional tests to improve the validity of the results of image sentiment analysis. The sentiment analysis techniques based on machine learning are very promising for predicting, classifying, and identifying the sentimental meaning of an image. However, to the best of our knowledge, no study has examined the validity of these technologies. Thus, five coders were invited to participate in this study. We presented them with 323 thumbnails and assigned them to score each for valence and arousal. Then we averaged the scores of the five coders and compared the results with those of Complura and IBM Watson. Correlation analysis between the two results showed that both valence (Pearson $r=0.353$, p value <0.01) and arousal (Pearson $r=0.358$, p value <0.01) were significant. This result is meaningful as the technique of image sentiment analysis is the initial stage [49]. That is, the results of the image sentiment analysis software based on machine learning have validity.

4.2.2 Title elements: text sentiment analysis

Natural language processing technology has been developed continuously; however, the Korean language presents a challenge. Various studies have been conducted to solve this problem [50]. Among them, Open Hangul, in which the valence dictionary is constructed through collective intelligence, is representative [50]. Open Hangul applies the concept of folksonomy, which is a way to classify valence and increase the efficiency of collective intelligence. More than 35,000 Korean words have been used to create a valence dictionary. Open Hangul was used as a representative valence dictionary of Korean for research by using news content and blog review analysis [51]. By using the Open Hangeul API, we could estimate the positive and negative sentiment value of the text. We used this to analyze the valence of video titles (text).

Next, the title's arousal score was derived from a customized arousal dictionary (there is no Korean sentiment dictionary for arousal). Arousal analysis of text was based on the sentiment polarity of a word that is the minimum unit of a sentence. After construction of a sentiment dictionary with a predefined sensibility polarity of words, the sentiment of sentences can be classified according to the emotional polarity of the words appearing in the newly developed document [52]. It is important to create sentiment dictionaries to analyze text sentiment. A typical example is the Affective Norms for English Words (ANEW), which is a kind of sentiment word dictionary designed to classify the sentiment of words [41].

ANEW is a dictionary of sentiment from words in three dimensions. Each word has three scores (valence, arousal, and dominance) and each score is between 1 and 10 points. These scores are based on the emotions felt by the surveyors for each word and the average of these scores. Based on the results, we developed a sentiment dictionary for arousal in this study. We extracted a total of 811 words from video titles and constructed an arousal dictionary from arousal scores produced by three coders who used the ANEW method [41]. Based on the Korean sentiment dictionary thus constructed, we calculated the degree of arousal of each title. We used R×64 3.2.5 for the programming language and the Korean Natural Language Processing package for Korean language processing.

4.3 Descriptive statistics and econometric model specification

4.3.1 Descriptive statistics

The dependent variable, *Selection* (of a video clip), was obtained through the following procedure. First, we obtained log data from both PC and mobile devices. The size of mobile log data collected from our study was 169,604 (82.2%) and the size of PC log data was 36,617 (17.8%). The log data has each user's front page access record (number of page views) and selected video record (number of clicks of a video). If a video was not selected from the user, then the selected clip record in the dataset was empty (i.e., null). The variable *Selection* was calculated by dividing the number of clicks of a video by the number of page views on a recommended date as a ratio. In other words, *Selection* refers to the ratio of user exposure to selection per video.

The variable *View Count* was indicated as the number of video views displayed on the video list on a recommended date. Another variable *Like Count* was operationalized as the number of video likes in the same manner as the *View Count*. The variable *Order* was coded as one from the top of the list of recommended videos, for instance, as 10 for the lowest on the list. As for control variables, we coded the *Time Gap* variable by subtracting the uploaded date from the video's recommended date. The target context, S-Service, typically uploads video clips to the service within a few hours after the corresponding episodes, including when the video clips are broadcast on television. Some of them are recommended on the front page of the service. *Video Length* was operationalized as the video's length displayed on the video list. Finally, we classified each type of video into the categories of soap opera, entertainment, and documentary based on video meta-data and created two dummy variables (Table 2).

4.3.2 Econometric model specification

We used a total of 323 videos in the analysis. We applied a logit-transformed *Selection* after checking the distributions of variables. For proportion measure, the value is always the predicted positive number and constrained to a maximum of 1. The logit transformation (i.e., log-odds) can deal with sensitivities. We also normalized the all independent variable to reduce nonlinearity in this study model. We

Table 2 Descriptive statistics

Variable	Description	Mean	SD
M_Selection	Indicates click ratio of a video by users from mobile log data (i.e., clicks of the video per page view on the recommended date)	0.005	0.003
P_Selection	Indicates click ratio of a video by users from PC log data (i.e., clicks of the video per page view on the recommended date)	0.005	0.004
I_Valence	Indicates the thumbnail's valence score by image mining (i.e., image valence)	3.545	0.880
I_Arousal	Indicates the thumbnail's arousal score by image mining (i.e., image arousal)	0.102	0.303
T_Valence	Indicates the title's sentiment score by text mining (i.e., text valence)	0.081	0.687
T_Arousal	Indicates the title's arousal score by text mining (i.e., text arousal)	20.786	7.338
Order	Indicates the serial position in the video list	5.647	2.806
View Count	Indicates the video play count on the recommended date	168,264.200	289,610.600
Like Count	Indicates the Like Count on the recommended date	700.802	1033.459
Time Gap	Indicating how many days passed from upload date to recommended date (i.e., recommend date–upload date)	1.920	6.271
Video Length	Indicates the length of the video (in seconds)	4.709	0.554
Genre_S	Indicates dummy variable of the genre of the video: 0 = other genres; 1 = soap opera	0.647	0.479
Genre_E	Indicates dummy variable of the genre of the video: 0 = other genres; 1 = entertainment	0.325	0.469

conducted correlation analysis for each variable included in this study (see “Appendix A”). Among them, the correlation coefficient of *View Count* and *Like Count* were high at 0.760 (p value < 0.01). Therefore, we dropped *Like Count* to minimize multicollinearity risk and to study rigorously.

Formula 2 describes the econometric model of this study. $Selection_{ij}$ refers to the selection of video clip j per device (i.e., i is *PC* or *Mobile*). In this study, $\mathrm{logit}\left(Selection_{ij}\right)$ is a dependent variable, β is the regression coefficient of the explanatory variable, γ is the regression coefficient of the control variable, and ε is the error term.

$$\mathrm{logit}\left(Y_{ij}\right) = \ln\left(\frac{Selection_{ij}}{1 - Selection_{ij}}\right), \tag{1}$$

$$\begin{aligned}\mathrm{logit}\left(Selection_{ij}\right) = {} & \beta_0 + \beta_1 I\_Valence_j + \beta_2 I\_Arousal_j + \beta_3 T\_Valence_j \\ & + \beta_4 T\_Arousal_j + \beta_5 Order_i + \beta_6 ViewCount_j + \sum_{1}^{k} \gamma_k Controls_j + \varepsilon_j\end{aligned} \tag{2}$$

5 Test results

5.1 Main results

We performed tests according to Formula (2) to determine if there is heteroskedasticity. The test results show that this model rejected homoskedasticity at the 1% significance level. In other words, this model is likely to have heteroskedasticity. The problem of heteroskedasticity cannot be solved through ordinary least squares analysis [53]. Therefore, we applied generalized least squares (GLS) regression analysis to test the hypotheses.

In Table 3, Models (3) and (4) represent the results in the PC context and mobile context as the logit-transformed dependent variable (hereafter, DV). We then check robustness to a different specification for the baseline. Table 3, Models (1) and (2) check that our results of variables affecting non-logit-transformed DV, motivated by the work of Xu and Lee [54]. The results between the models are similar overall.

Model (4) is the main model in which the coefficients of all key variables were statistically significant. The test results explain, first, that the preview content factors affect the selection of video in a mobile context. As other variables are constant, the odds ratio for the *Valence* of a thumbnail decrease from 1.0 to 0.905 (= $e^{-0.100}$), but *Arousal* of a thumbnail increase from 1.0 to 1.060 (= $e^{0.059}$). As for a title, the odds ratio for both *Valence* and *Arousal* are 1.069 (= $e^{0.067}$), 1.109 (= $e^{0.103}$) and significant. Therefore, H2, H3, and H4 are all supported, but H1 is rejected. On the other hand, as can be seen from the result of Model (3), the *Valence* of the thumbnail and both *Valence* and *Arousal* of the title were not significant, but the thumbnail’s *Arousal* was significant in the PC context.

Second, the variables related to the context effect greatly influence video selection. In the main model results, the odds ratio for *Order* of a video is 0.629

Table 3 Main results

	DV[a]				Logit-transformed DV			
	PC-Model (1)		Mobile-Model (2)		PC-Model (3)		Mobile-Model (4)	
	Coefficient (β)	SE	Coefficient ((β)	SE	Odds Ratio (e^{β})	SE	Odds Ratio (e^{β})	SE
I_Valence	0.010	(0.020)	−0.033**	(0.015)	0.980	(0.043)	0.905***	(0.033)
I_Arousal	0.062**	(0.025)	0.030*	(0.017)	1.130***	(0.041)	1.060*[b]	(0.031)
T_Valence	0.005	(0.018)	0.036***	(0.014)	1.022	(0.040)	1.069**	(0.031)
T_Arousal	0.019	(0.020)	0.040***	(0.014)	1.042	(0.039)	1.109***	(0.032)
Order	−0.105***	(0.020)	−0.211***	(0.016)	0.796***	(0.039)	0.629***	(0.029)
View Count	0.112***	(0.032)	0.116***	(0.020)	1.264***	(0.058)	1.328***	(0.038)
Time gap	0.008	(0.020)	−0.048***	(0.009)	0.994	(0.036)	0.866***	(0.017)
Video Length	0.052**	(0.025)	0.028*	(0.014)	1.089**	(0.040)	1.087**	(0.034)
Genre_S	0.012	(0.042)	0.030	(0.042)	1.011	(0.104)	1.129	(0.074)
Genre_E	0.119***	(0.044)	−0.010	(0.042)	1.272**	(0.104)	1.015	(0.076)
Constant	0.492***	(0.019)	0.465***	(0.014)	0.004***	(0.038)	0.004***	(0.030)
R^2	0.234		0.515		0.242		0.519	

***, **, and * denote significance at 0.1%, 1% and 5%, respectively

[a]DV is measured in 10^{-2}

[b]p value = 0.059

($= e^{-0.464}$) and significant. That is, even after controlling for other variables, the odds of the lower serial position is 37.1% lower than in the upper serial position. The odds ratio for popularity cue *View Count* is 1.328 ($= e^{0.284}$) and significant. Thus, both H5 and H6 are supported. In the PC environment, the odds ratio for *View Count* and *Order* of are significant, just the same as in the mobile context.

Finally, we obtained in the main model additional interesting results related to the testing of control variables. The odds ratio for the *Time Gap* decrease from 1.0 to 0.866 ($= e^{-0.144}$), but *Video Length* increases from 1.0 to 1.087 ($= e^{0.083}$) in the mobile context. However, the odds ratio for both *Genre_S* and *Genre_E* are not significant in the main model. The value of R^2 was 0.519 for Model (4), which is the result for mobiles, and 0.242 for Model (2), which is the result for PCs. To summarize, the factors affecting video selection are different in the mobile and PC environments.

5.2 Robustness check: two-stage least squares (2SLS) regression

Endogeneity issues can arise in a model. In particular, *View Count* is suspected of endogeneity because of the relationship with dependent variables. When a user selects a video clip, the number of plays (i.e., view count) can increase. Therefore, we conducted a two-stage least squares (2SLS) regression with an instrumental variable to address this endogeneity problem. The instrumental variable should fulfill two criteria: (1) it should have high correlation with the endogenous variable and (2) it should have been no partial effect on the dependent variable [55]. To satisfy conditions, we selected *Others Views* as an instrumental variable in keeping with a similar study [56]. *Others Views* refers to an average number of video clip views of TV shows that are part of the video. S-Service displays the name of the TV show that belongs to each video clip. Thus, we obtained all the video clip views of the TV show that the video belongs to in the last month from the recommended day. We then calculated the average number of views of the rest of the video except the video used in the main model. This variable was related to the *View Count* (i.e., endogenous variable) and have no partial effect on *Selection* (i.e., the dependent variable). The econometric analysis model of 2SLS regression is shown as follows:

$$View\ Count_j = \beta_0 + \beta_1 Others\ Views_j + \varepsilon_j \tag{3}$$

$$\begin{aligned} \mathrm{logit}\left(Selection_{ij}\right) = \beta_0 &+ \beta_1 I\_Valence_j + \beta_2 I\_Arousal_j + \beta_3 T\_Valence_j \\ &+ \beta_4 T\_Arousal_j + \beta_5 Order_j + \beta_6 \log\left(\widehat{View\ Count_j}\right) \\ &+ \sum_1^k \gamma_k Controls_j + \varepsilon_j, \end{aligned} \tag{4}$$

The results of 2SLS are similar to the main results of this study (see "Appendix B"). As a result, this study model implies that robust results are derived.

6 Discussion and implications

6.1 Discussion of findings

This study has four key findings related to the effects of content and context factors on video selection in a mobile environment. First, we found through image sentiment analysis that sentimental thumbnails affect video selection. We found that arousal thumbnails have a positive effect on video selection. However, contrary to Hypothesis 1, negative thumbnails have a positive effect on video selection, not positive thumbnails. A possible theoretical reason for this divergence may be that negative images attract people's attention more. According to prior studies, the fact that valence images draw more attention than images with no emotional content was shown clearly [26, 57]. However, there has been controversy among the prior studies about whether negative or positive images are more effective. The main argument of preview studies is that positive images affect user attention and behavior by making the user feel positive [8, 21, 22]. Other researchers argue against this. According to Santos et al. [57], negative images attract more attention. They conducted eye-tracking and electroencephalographic experiments on 40 adults aged 18–25 years. The results showed that negative images receive more attention. Similarly, in our study, negative thumbnails had a positive effect on video selection [57]. In other words, video thumbnails that convey a low level of valence and a high level of arousal also arouse excitement and attraction that motivates the selection of a video.

Second, this study found that sentimental titles affect a user's selection of videos in a mobile context. We used a text mining technique to assess the level of sentiment in video titles. According to the results, a video's title has a positive effect on video selection as the level of valence or arousal increases. In other words, video titles that are more pleasant or more exciting promote the selection of the video. On the other hand, the sentiment of the title on PC did not affect video selection. This finding is consistent with the model of attention capture and transfer [16], especially the bottom–up mechanism [19]. That is, the two content factors (thumbnail and title) capture users' attention through valence and arousal.

Third, the results show that the two context factors (popularity cue and serial position) influence video selection in a mobile context. The serial position in the video list also affects selection more in the mobile context than in the PC. The higher the serial position of the video, the more positive the video selection. In other words, the order influences video selection [33]. This finding is consistent with the primacy effect [32]. We also found that the higher the number of views, the higher the video selection, which is consistent with the bandwagon effect [34]. Thus, it affects users' herding behavior in video clip selection in both the mobile and PC contexts.

We found some other interesting results. Both the length and recency of a video have positive effects on selection. In the target research context, which is similar to the YouTube context, users can watch each video clip after seeing an average of about 15 s of advertisement. That is, users must spend about 15 s as a cost to watch each video.

Therefore, viewers prefer a longer video clip[4] as a benefit, given the 15-s cost, from the utility maximization perspective [43]. In addition, users cannot know the upload date of a video because of the screen limitation, but it is possible to deduce it through the title of a video. For example, in some videos, the title includes the number of episodes of the TV show (e.g., [episode 12] The Return of Superman). Users seem to perceive value, i.e., epistemic value [58], from a recent video because it may have the capability to arouse curiosity, provide novelty, and satisfy a desire for new content. Such value may lead users to select recent videos from the customer value perspective [58].

6.2 Limitations and future research

We recognize that this study has some limitations. First, we investigated only context and content factors and their effects on video selection from the perspective of heuristic route processing and using the bottom–up mechanism [16] from dual process theory [9]. The dual process theory explains the systematic processing perspective as well in decision making. Future studies can consider examining video selection from the systematic processing perspective with the top–down mechanism and the model of attention capture and transfer.

Second, the image mining technology used in this study may have its limitations. Big data techniques, including image mining, will continue to evolve. However, image mining technique is no match for human perceptions and poses various problems in practical use [49]. Besides, the sentiment analysis used in prior studies has also produced conflicting results [59]. However, improper or inaccurate emotional analysis techniques may account for these inconsistencies [60]. It would be valuable in future research to use big data technology to compare the accuracy of earlier sentiment scores with those of this study.

Third, other external environmental factors may exist that can affect video selection. The external environment may affect selection before the user connects to the video service. Recommendations from friends, SNS recommendations, and rankings of real-time queries are all examples of such external interference. Moreover, video clip service recently provides 2–3s "video previews" when users hover their mice on them, that might affect users' video selection. However, these variables are beyond the scope of this study because they are difficult to measure and determine if they have real impacts. We look forward to finding additional variables in future studies.

6.3 Implications for research

This study has several implications for research, especially because it is the first to empirically investigate which context and content factors affect video selection by users of mobile devices. These are (1) using dual process theory to address both empirically and theoretically a gap in previous studies on video selection on mobile devices [9],

[4] Note that the length of the videos in our research environment did not exceed 10 min.

and also to apply the model of attention capture and transfer [16]; (2) demonstrating how sentimental preview of content affects video selection through the use of sentiment analysis of thumbnails and titles of video clips; and (3) explaining the role and effects of content and context factors on selection of video clips in a mobile device context.

The main implication of this study for research is the application of dual process theory and the model of attention capture and transfer in examining what drives video selection in the mobile environment. With an increasing number of videos viewed in the mobile environment, a few studies have started to explore what drives video selection [10, 12]; however, none have considered video selection about the device used, i.e., mobile or PC. Because mobile devices are small, they can only display limited amounts of preview information and elements of preview content. Based on the application of the heuristic route in dual process theory, a major contribution of the present study is its identification of content factors from the perspective of a bottom–up mechanism with the model of attention capture and transfer, and its consideration of context factors from the perspectives of the bandwagon [34] and order effects [33]. Based on the two content elements (thumbnail and title) and two context elements (popularity cue and serial position), we identified six factors that are largely absent from the previous studies: thumbnail valence/arousal, title valence/arousal, serial position, and popularity cues. This study enriches the theories in that the environmental cues that affect users' selection are detailed in the heuristic perspective.

Second, this study also adds value to the literature by demonstrating through sentiment analysis of the thumbnails and titles of each video clip studied how sentimental preview content affects video selection. Prior research concentrated on the presence or absence of video preview content [10] or the format and type of content components [10, 18]. However, going beyond previous research, it is important to examine how to expand preview content in the latest mobile environment. Emotional preview content greatly influences a user's selection of a video [25]. Thus, this study contributes to understanding the effect of content factors on video selection by using sentiment analysis of the thumbnails and titles. The results of this research support previous findings that emotional content is more attractive than neutral content [26, 27].

Finally, this study contributes to the literature by explaining the role and effects of content and context factors on the selection of video clips in the mobile device context. This study analyzed the factors affecting video selection by using the actual data and meta-data of each video clip collected from a leading video service in South Korea. Specifically, the selection of videos (DV) differs from previous research. Previous studies used a cumulative view count exposed on the service screen [10, 12]. However, the cumulative number of views is the total sum of selections from the front, search, and subcategory pages. Notably, heuristic processing may not occur in the case of an organic search (i.e., with user purpose).

On the other hand, this study presented empirical results through the log data of actual videos selected on a front page. The test results explain that from the context perspective, the number of views of a video clip and its serial position affects its selection. The test results also explain that from a content perspective, both the valence of a title and the arousal by a thumbnail and title increase the selection of a video. In this way, this study has explained what and how content and context factors affect video selection in the mobile device context.

6.4 Implications for practice

The results of this study also have several implications for practice, especially for providers of video services. First, from a content perspective, this study provides a production guide for video titles and thumbnails. It may be helpful to select a video with attractive preview content when selecting a recommendation video on the front page of a mobile device. For example, for a thumbnail, one with a crying character (negative) or sexy image (arousal) may attract users' attention and help them decide to select the video. As for titles, we suggest they use positive and arousal words such as "kiss," "back hug," "love," and "first experience."

Second, from the context perspective, we suggest two context factors (popularity cue and serial position) to consider when recommending videos from a mobile video service. Video service providers can leverage the order and popularity cues for videos appropriately when recommending them on their front page. Therefore, videos with high viewer counts and high-ranking recommendations may stimulate a user to select them. In the case of YouTube, videos are recommended in the order of their recommendation score (e.g., higher view counts) in the top N format [4].

Third, this study provides additional guidance regarding the design and list of videos on the front page of mobile devices. Our study explains that users tend to select longer and more recent videos. That is, more people may click on a video if it is displayed for a long time and with recent episodes at the top of the video list on the front page of a mobile-based video service. Thus, the results of this study can guide the design of a mobile video service, especially the display of video clips on the front page, which can lead to increased revenue for the service provider.

In conclusion, this study can be used as a basic step in researching the role of preview content and context factors that affect video selection. More importantly, images and text processing methods that can be computed in near-real-time are theoretically and practically exploitable. Video service providers and content providers can consider our findings as a way to design and recommend videos to users on the front page. We also expect our research results to be useful for most content services that use a preview format.

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Appendix

Appendix A Correlation matrix

		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
M_Selection	V1	–									
I_Valence	V2	0.010	–								
I_Arousal	V3	0.146***	0.012	–							
T_Valence	V4	0.169***	0.136**	0.096*	–						
T_Arousal	V5	0.080	−0.062	0.108**	0.051	–					
Order	V6	−0.601***	−0.053	−0.038	−0.015	0.050	–				
View Count	V7	0.263***	0.172***	0.059	0.191***	−0.063	0.035	–			
Like Count	V8	0.307***	0.110**	0.109*	0.143***	−0.043	0.029	0.760***	–		
Time Gap	V9	−0.002	−0.014	0.024	0.131**	0.044	0.013	0.379***	0.212***	–	
Video Length	V10	−0.039	−0.099*	−0.084	0.005	0.165***	0.035	−0.304***	−0.139**	−0.021	–
P_Selection	V1	–									
I_Valence	V2	0.055***	–								
I_Arousal	V3	0.154	0.012	–							
T_Valence	V4	0.083	0.136**	0.096*	–						
T_Arousal	V5	0.089	−0.062	0.108*	0.051	–					
Order	V6	−0.245***	−0.053	−0.038	−0.015	0.050	–				
View Count	V7	0.210***	0.172**	0.059	0.191***	−0.063	0.035	–			
Like Count	V8	0.227***	0.110**	0.109**	0.143***	−0.043	0.029	0.760***	–		
Time Gap	V9	0.130**	−0.014	0.024	0.131	0.044	0.013	0.379***	0.212	–	
Video Length	V10	−0.035	−0.135**	−0.068	−0.014	0.154***	0.000	−0.462***	−0.245***	−0.076	–

***, **, and * denote significance at 1%, 5% and 10%, respectively. To aid understanding, the results of the two genre dummy variables are not presented

Appendix B 2SLS result with instrument variable (*Others views*)

Variable	2SLS Model DV: *logit (P_Selection)*		2SLS Model DV: *logit (M_Selection)*	
	Odds Ratio	SE	Odds Ratio	SE
View Count	1.371***	(0.087)	1.443***	(0.068)
I_Valence	0.971	(0.043)	0.896***	(0.033)
I_Arousal	1.128***	(0.040)	1.059*	(0.030)
T_Valence	1.012	(0.041)	1.058*	(0.031)
T_Arousal	1.045	(0.039)	1.112***	(0.031)
Order	0.792***	(0.040)	0.624***	(0.029)
Time Gap	0.965	(0.068)	0.840***	(0.040)
Video Length	1.112**	(0.045)	1.110***	(0.036)
Genre_S	0.997	(0.104)	1.113	(0.069)
Genre_E	1.269**	(0.103)	1.012	(0.071)
Constant	0.004***	(0.038)	0.004***	(0.030)
R^2	0.234		0.512	

***, **, and * denote significance at 0.1%, 1% and 5%, respectively

References

1. IAB Research. (2015). One in four U.S. adults watches original digital video, According to IAB Research. *IAB*. Retrieved July 23, 2017 from https://www.iab.com/insights/one-in-four-u-s-adults-watches-original-digital-video-according-to-iab-research/.
2. Statista. (2018). U.S. YouTube video ad advertising revenues 2018| Statistic. *Statista*. Retrieved August 28, 2018 from https://www.statista.com/statistics/248859/youtube-us-net-video-advertising-revenues/.
3. Crompton, J. L., & Ankomah, P. K. (1993). Choice set propositions in destination decisions. *Annals of Tourism Research, 20*(3), 461–476.
4. Davidson, J., Liebald, B., Liu, J., Nandy, P., Van Vleet, T., Gargi, U., et al. (2010). The YouTube video recommendation system. In *Proceedings of the fourth ACM conference on recommender systems* (pp. 293–296). ACM.
5. Ghose, A., Goldfarb, A., & Han, S. P. (2012). How is the mobile Internet different? Search costs and local activities. *Information Systems Research, 24*(3), 613–631.
6. Weaver, K. A., Yang, H., Zhai, S., & Pierce, J. (2011). Understanding information preview in mobile email processing. In *Proceedings of the 13th international conference on human computer interaction with mobile devices and services* (pp. 303–312). ACM.
7. De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing, 26*(2), 83–91.
8. Shin, D., He, S., Lee, G. M., Whinston, A. B., Cetintas, S., & Lee, K. -C. (2016). Content Complexity, Similarity, and Consistency in Social Media: A Deep Learning Approach. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2830377.
9. Groves, P. M., & Thompson, R. F. (1970). Habituation: A dual-process theory. *Psychological Review, 77*(5), 419.
10. Fu, W. W., & Sim, C. C. (2011). Aggregate bandwagon effect on online videos' viewership: Value uncertainty, popularity cues, and heuristics. *Journal of the American Society for Information Science and Technology, 62*(12), 2382–2395.
11. Hilligoss, B., & Rieh, S. Y. (2008). Developing a unifying framework of credibility assessment: Construct, heuristics, and interaction in context. *Information Processing and Management, 44*(4), 1467–1484.

12. Fu, W. W. (2012). Selecting online videos from graphics, text, and view counts: The moderation of popularity bandwagons. *Journal of Computer-Mediated Communication, 18*(1), 46–61.
13. Cheung, C. M., Xiao, B. S., & Liu, I. L. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems, 65,* 50–58.
14. Susarla, A., Oh, J.-H., & Tan, Y. (2012). Social networks and the diffusion of user-generated content: Evidence from YouTube. *Information Systems Research, 23*(1), 23–41.
15. Hsieh, J.-K., Hsieh, Y.-C., & Tang, Y.-C. (2012). Exploring the disseminating behaviors of eWOM marketing: Persuasion in online video. *Electronic Commerce Research, 12*(2), 201–224.
16. Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing, 68*(2), 36–50.
17. Zhou, S., & Guo, B. (2017). The order effect on online review helpfulness: A social influence perspective. *Decision Support Systems, 93,* 77–87.
18. Dewan, S., Ho, Y.-J., & Ramaprasad, J. (2017). Popularity or proximity: Characterizing the nature of social influence in an online music community. *Information Systems Research, 28*(1), 117–136.
19. Yantis, S. (2000). Goal-directed and stimulus-driven determinants of attentional control. *Attention and Performance, 18,* 73–103.
20. Yantis, S., & Jonides, J. (1990). Abrupt visual onsets and selective attention: Voluntary versus automatic allocation. *Journal of Experimental Psychology: Human Perception and Performance, 16*(1), 121.
21. Ang, S. H., & Low, S. Y. (2000). Exploring the dimensions of Ad creativity. *Psychology and Marketing, 17*(10), 835–854.
22. Berger, J., & Milkman, K. (2010). Social transmission, emotion, and the virality of online content. *Wharton Research Paper, 106,* 1–52.
23. Lane, R. D., Chua, P. M., & Dolan, R. J. (1999). Common effects of emotional valence, arousal and attention on neural activation during visual processing of pictures. *Neuropsychologia, 37*(9), 989–997.
24. Schupp, H. T., Flaisch, T., Stockburger, J., & Junghöfer, M. (2006). Emotion and attention: Event-related brain potential studies. *Progress in Brain Research, 156,* 31–51.
25. Wiens, S., Molapour, T., Overfeld, J., & Sand, A. (2012). High negative valence does not protect emotional event-related potentials from spatial inattention and perceptual load. *Cognitive, Affective, and Behavioral Neuroscience, 12*(1), 151–160.
26. Kensinger, E. A., & Schacter, D. L. (2006). Processing emotional pictures and words: effects of valence and arousal. *Cognitive, Affective, and Behavioral Neuroscience, 6*(2), 110–126.
27. Bayer, M., Sommer, W., & Schacht, A. (2010). Reading emotional words within sentences: The impact of arousal and valence on event-related potentials. *International Journal of Psychophysiology, 78*(3), 299–307.
28. Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*(6), 1161–1178.
29. Barua, A., Ravindran, S., & Whinston, A. B. (1997). Efficient Selection of Suppliers over the Internet. *Journal of Management Information Systems, 13*(4), 117–137.
30. Zhang, W., Liu, C., Wang, Z., Li, G., Huang, Q., & Gao, W. (2014). Web video thumbnail recommendation with content-aware analysis and query-sensitive matching. *Multimedia Tools and Applications, 73*(1), 547–571.
31. Liebe, U., Hundeshagen, C., Beyer, H., & von Cramon-Taubadel, S. (2016). Context effects and the temporal stability of stated preferences. *Social Science Research, 60,* 135–147.
32. Haugtvedt, C. P., & Wegener, D. T. (1994). Message order effects in persuasion: An attitude strength perspective. *Journal of Consumer Research, 21*(1), 205–218.
33. Hogarth, R. M., & Einhorn, H. J. (1992). Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology, 24*(1), 1–55.
34. Leibenstein, H. (1950). Bandwagon, snob, and Veblen effects in the theory of consumers' demand. *The Quarterly Journal of Economics, 64,* 183–207.
35. Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107,* 797–817.
36. Dewan, S., & Ramaprasad, J. (2012). Research note: Music blogging, online sampling, and the long tail. *Information Systems Research, 23*(3-part-2), 1056–1067.
37. Walther, J. B., & Jang, J. (2012). Communication processes in participatory websites. *Journal of Computer-Mediated Communication, 18*(1), 2–15.

38. Rout, J. K., Choo, K.-K. R., Dash, A. K., Bakshi, S., Jena, S. K., & Williams, K. L. (2018). A model for sentiment and emotion analysis of unstructured social media text. *Electronic Commerce Research, 18*(1), 181–199.
39. Jenkins, B. (2011). Consumer sharing of viral video advertisements: A look into message and creative strategy typologies and emotional content. *A Capstone Project*.
40. Das, E., Galekh, M., & Vonkeman, C. (2015). Is sexy better than funny? Disentangling the persuasive effects of pleasure and arousal across sex and humour appeals. *International Journal of Advertising, 34*(3), 406–420.
41. Bradley, M. M., & Lang, P. J. (1999). *Affective norms for English words (ANEW): Instruction manual and affective ratings*. Technical report C-1, the center for research in psychophysiology, Florida: University of Florida.
42. Miller, H. J. (1993). Consumer search and retail analysis. *Journal of Retailing, 69*(2), 160–192.
43. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society, 47,* 263–291.
44. Xu, Y. C., & Kim, H.-W. (2008). Order effect and vendor inspection in online comparison shopping. *Journal of Retailing, 84*(4), 477–486.
45. Zhou, R., Khemmarat, S., Gao, L., Wan, J., & Zhang, J. (2016). How YouTube videos are discovered and its impact on video views. *Multimedia Tools and Applications, 75*(10), 6035–6058.
46. Liu, H., Jou, B., Chen, T., Topkara, M., Pappas, N., Redi, M., & Chang, S. -F. (2016). Complura: Exploring and leveraging a large-scale multilingual visual sentiment ontology. In *Proceedings of the 2016 ACM on international conference on multimedia retrieval* (pp. 417–420). ACM.
47. Borth, D., Ji, R., Chen, T., Breuel, T., & Chang, S. -F. (2013). Large-scale visual sentiment ontology and detectors using adjective noun pairs. In *Proceedings of the 21st ACM international conference on Multimedia* (pp. 223–232). ACM.
48. Kurdi, B., Lozano, S., & Banaji, M. R. (2017). Introducing the open affective standardized image set (OASIS). *Behavior Research Methods, 49*(2), 457–470.
49. Cao, D., Ji, R., Lin, D., & Li, S. (2016). Visual sentiment topic model based microblog image sentiment analysis. *Multimedia Tools and Applications, 75*(15), 8955–8968.
50. An, A., & Kim, H.-W. (2015). Building a Korean Sentiment Lexicon Using Collective Intelligence. *Journal of Intelligence and Information Systems, 21*(2), 49–67.
51. Kim, S., Kwon, S., & Kim, J. (2015). Building sentiment dictionary and polarity classification of blog review by using elastic net. *Communications of the Korean Institute of Information Scientists and Engineers*, 2015(12), 639–641.
52. Kim, S., & Kim, N. (2014). A Study on the effect of using sentiment lexicon in opinion classification. *Journal of Intelligence and Information Systems, 20*(1), 133–148.
53. Pfeffer, J., & Davis-Blake, A. (1986). Administrative succession and organizational performance: How administrator experience mediates the succession effect. *Academy of Management Journal, 29*(1), 72–83.
54. Xu, X., & Lee, L. (2015). A spatial autoregressive model with a nonlinear transformation of the dependent variable. *Journal of Econometrics, 186*(1), 1–18.
55. Rahman, M., Rodríguez-Serrano, M. Á., & Lambkin, M. (2017). Corporate social responsibility and marketing performance: The moderating role of advertising intensity. *Journal of Advertising Research, 57*(4), 368–378.
56. Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics, 31,* 395–421.
57. Santos, M. A. D., Lobos, C., Muñoz, N., Romero, D., & Sanhueza, R. (2017). The influence of image valence on the attention paid to charity advertising. *Journal of Nonprofit and Public Sector Marketing*, *0*(0), 1–18.
58. Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research, 22*(2), 159–170.
59. Zhang, Z., Li, X., & Chen, Y. (2012). Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews. *ACM Transactions on Management Information Systems (TMIS), 3*(1), 5.
60. Liang, T.-P., Li, X., Yang, C.-T., & Wang, M. (2015). What in consumer reviews affects the sales of mobile apps: A multifacet sentiment analysis approach. *International Journal of Electronic Commerce, 20*(2), 236–260.