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ORIGINAL ARTICLE

Motivational Processing and Choice Behavior During Television Viewing: An Integrative Dynamic Approach

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This study was designed to further our understanding of the central role of motivational activation in mediated information processing and media choice. To do this, a dynamic model was developed to formalize the dynamic effects of three basic motivational input variables (arousing content, positivity, and negativity) on four physiological output measures (heart rate, skin conductance level, corrugator activity, and zygomatic activity) and a behavioral choice measure of television channel selection. The input and output variables were selected based on extensive theoretical and empirical research that has explicated static relationships among these variables. In general, the findings of the dynamic modeling approach were consistent with the previous literature using traditional static statistical methods. However, this study also theoretically extended the previous work.

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For almost half a century, it has been generally acknowledged that communication is a dynamic process occurring over time (Berlo, 1960). There has, however, been "very little general, systematic examination of dynamic processes in the specific context of communication" (VanLear & Watt, 1996, p. 3). This research seeks to help correct this situation by introducing and testing a set of dynamic models that provide an integrative conceptual framework of motivational processing and channel choice behavior in the context of television viewing.

The dynamic models being proposed are built on psychological theories of motivational processing (e.g., Cacioppo, Gardner, & Berntson, 1999; Lang, Bradley, & Cuthbert, 1997; Williams, 2006) and Lang's (2000, 2006a, 2006b) limited capacity theory of motivated processing in a mediated environment. The models emphasize motivational activation as a fundamental factor in information processing and choice

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behavior and aim to explain how the effects evolve dynamically. Hence, this set of models is called the dynamic motivational activation (DMA) model. In this study, the model is tested using real-time data indicative of motivational inputs, emotional responses, cognitive effort, and channel choices.

Review of the theories

Motivational processing

Emotion plays a central role in our experience (Prinz, 2004), including mediated experience. However, the adaptive functions, organization, and operating characteristics of our emotion system point us toward the even more fundamental role of motivation (e.g., P. Lang et al., 1997; Plutchik, 1984). This article takes the following basic stance on studying the motivational processing of mediated messages: (a) It follows the dimensional approach in emotion research and considers that emotion is fundamentally organized around the appetitive and aversive motivational systems designed by evolution to promote survival (e.g., Larsen, Norris, & Cacioppo, 2003). Psychophysiological and neurophysiological research on emotion suggests that the autonomic and behavioral responses to emotional stimuli reflect the underlying neural and subcortical structures activated by the appetitive and aversive motivational systems; motivational activation prepares and facilitates an organism's appropriate interaction with the environment (for a review, see Berntson & Cacioppo, 2008; M. Bradley & P. Lang, 2000). Specifically, the dimensional approach posits that activation in the appetitive or aversive systems elicits pleasant or unpleasant emotion, which can be mapped onto a dimension or continuum of valence (from very pleasant to very unpleasant); the intensity of the activation determines the emotional arousal levels (from very calm to very arousing/aroused). These two dimensions, valence and arousal, have been useful in parsimoniously describing both emotional media content and media users' emotional experiences (Ravaja, 2004; Bolls, A. Lang, & Potter, 2001). (b) The two motivational systems are logically independent, although not necessarily statistically uncorrelated; the dynamic activations of these two systems appear to be variably synchronistic—their dynamic correlations can vary from -1 to 0 and sometimes can be positive, depending on the context (e.g., Zautra, Berkhof, & Nicolson, 2002). (c) The motivational processes operate not only in our everyday life but also during our experiences in the mediated world (P. Lang et al., 1997). Our programmed-by-evolution psychophysiological systems react to mediated messages as if they were real (A. Lang, 2000, 2006a, 2006b; Reeves & Nass, 1996).

A dynamic approach to understanding motivational processing

The primary theoretical importance of this study rests on its commitment to dynamic information processing models and methodology. A. Lang's (2006a, 2006b) limited capacity model of motivated mediated message processing (LC4MP) is a theoretical framework that applies a limited capacity information processing approach to mediated environments. It is supported by a great deal of empirical work using real-time psychophysiological data. It is based on explanations of information processing that are theorized to be modulated by motivational activation over time. However, its predictions are limited in the sense that only the directions of the information processing patterns, aggregated across time, can be proposed and tested. This limitation arises from the reliance on static methods, such as analysis of variance, for analyzing the data. The great potential to explicate the dynamic interactions between messages and individual responses cannot be realized unless formal (i.e., mathematical) dynamic models are employed. In other words, rich information about dynamic processes still remains hidden in real-time data due to the constraints of static analytical tools that aggregate the data over time (Beltrami, 1987; Luenberger, 1979). Therefore, formal dynamic modeling is the next logical step in developing the LC4MP to a truly dynamic level as required by this theoretical framework. This study is among the first efforts to do so (other efforts include a connectionist model of attention and memory proposed by S. Bradley, 2007; a stochastic model of media choices proposed by Wang, Busemeyer, & A. Lang, 2006).

The most general idea tested in this study is that key dependent variables (i.e., outputs) in information processing are causally influenced by motivational activation elicited by mediated emotional content (i.e., inputs). The DMA formalizes these multiple motivational inputs and outputs as a second-order linear stochastic system with lagged input effects and autoregressive residuals. Each of the outputs is influenced by three basic motivational input variables, their dynamic interactions, and feedback from its own previous responses. The feedback effect term is critical: It is responsible for the time it takes the physiological systems to be activated or deactivated with the changes in motivational inputs (e.g., Wang & A. Lang, 2006) as well as the cumulative effects of the inputs. This is discussed in detail in the section of *Hypothesized models*. To the authors' knowledge, this is the first attempt to build dynamic models explaining the causal influence of motivational inputs on physiological outputs across time. Previous research concerning time series models only involved analyses of the physiological dependent variables across time which is mostly descriptive.

An integrative approach to the black box of motivational processing

Emotional media content elicits motivational activation in individuals, which drives emotional experience. Although we cannot see directly into the black box of emotion and motivation, empirical research has developed a set of measures that we can use to infer what is happening in the box. P. Lang (1993) grouped measures of emotional experience into three output systems: (a) behavioral measures, including overt or functional behaviors and behavior modulations (e.g., fight, flight, and emotional modulation of task performance); (b) language measures, including expressive communication and evaluative report (e.g., verbal aggression, screams, and self-reported emotion); and (c) physiological measures, including reactions in the viscera (e.g., sweat glands, cardiovascular system, and tear ducts); somatic muscles (e.g., corrugator supercilii, zygomaticus major, and general action muscles); the respiration, endocrine, and immune system; and the brain.

If motivation is a fundamental principle in emotional experience (M. Bradley & P. Lang, 2000), it is necessary to understand the relationship between motivational activation and the different emotional output systems. It is a common understanding that these output systems vary in their action patterns to emotional stimuli, and both concordance and discordance exist among their reactions (M. Bradley & P. Lang, 2000). At least two lines of research demonstrate the diversity and complexity of emotional outputs. First, it has been observed that covariance among the output systems generally accounts for less than 10–15% of the variance (P. Lang, 1968; Mandler, Mandler, Kremen, & Sholiton, 1961). Second, the sensitivity and dynamics of those output systems vary across individuals. For example, when people report emotional experiences, hypersensitive individuals are more likely to focus on their own internal physiological cues, whereas hyposensitive individuals are more likely to attend to environmental cues (Blascovich, 1990). The complexity in these studies highlights why the task of developing an integrative explanation of the variation in patterns within and among the three emotional output systems remains "the central challenge to theory and research in emotion" (M. Bradley & P. Lang, 2000, p. 245). Meanwhile, these studies also suggest a possible response to this challenge—that is, through the simultaneous measurement and examination of multiple motivational output systems.

This study follows this suggestion and simultaneously measures the physiological and behavioral outputs of message processing as a function of motivationally relevant media content. All the dependent variables are recorded continuously while viewing emotional television content and analyzed using time series models.

Hypothesized models

General hypotheses of DMA and specific models of physiological responses

The primary hypothesis of this study is that the temporal variance in psychophysiological responses and channel-changing behavior during television viewing can be explained by the dynamic effects of three motivational inputs—the level of arousing content, positivity, and negativity in the media content (Hypothesis 1).

In addition, this study emphasizes that the effects of the three motivational inputs will be dynamic. The effects of motivational inputs do not occur or cease instantaneously, but instead, build up and ramp down over time (A. Lang, 2006a, 2006b; Wang & A. Lang, 2006). Also, the asymptotic level reached by the system and the final magnitude of any effect depend on dynamic feedback factors. That is, when a motivational input appears or increases, this onset or increase causes a change in the physiological system that accumulates across time to build up to an asymptotic level. When this motivational input is removed, the physiological system deactivates over time. In other words, the physiological response is determined not only by the current input but also by previous responses. Hence, we hypothesize that the physiological systems should have feedback effects (Hypothesis 2.1). However, in our review of the literature, we have discovered no studies that have investigated how many orders of feedback terms (i.e., time lags) are needed to catch the dynamic time course of physiological responses. A second-order system is proposed here for two major reasons. First, most time series analysis applications find two feedback terms to be sufficient to catch the dynamics in the systematic part of a time series model (c.f., higher order models used in modeling the errors; Boker & Wenger, 2007; Chatfield, 1999; Harvey, 1990; Warren, 2006) and higher order feedback terms as a systematic part of a model are rarely interpretable. Second, homeostasis of the physiological system (Stern, Ray, & Quigley, 2001) suggests that the system has the tendency and ability to remain in stable/equilibrium states, which is an inertial function; additionally, after changes caused by external or internal factors, the system can return to its original or resting state, which can be considered an oscillation function (Buzsáki, 2006). For dynamic systems, a first-order feedback term can produce the inertial effect, whereas a second-order feedback term can produce the oscillation effect. Therefore, the first- and second-order feedback terms will be used in our models and we will test whether these two feedback terms are sufficient to provide an account of the dynamics of the physiological systems (Hypothesis 2.2). It is worth mention that when the sampling interval is small enough to catch the variance of interest in the data, decreasing the sampling interval can affect coefficients and error terms in a time series model but does not change the function equation or the order of the dynamic system. That is, a second-order system will remain adequate even if the sampling interval is reduced. In this study, the sampling interval of model output data is 1 second. This sampling rate should be adequate for our modeling purpose because it is faster than the change rate of the input (i.e., motivational content from media) and also this rate is commonly used to analyze the physiological responses measured in this study.

In addition, it is expected that there is a time delay between an onset or a change in a motivational input and the physiological responses that it elicits. This is because it takes time for the motivational inputs to reach and activate physiological systems. Therefore, it is proposed that there will be time lags between the onset of the motivational inputs and the physiological responses (Hypothesis 3).

Dynamic theory-driven hypotheses are expressed formally as difference or differential equations. To systematically test the dynamic effects of the three motivational inputs on each physiological and behavior output, a second-order linear stochastic difference equation model with delayed input effects and with autoregressive error term is proposed. Basically, the proposed model is composed of two main parts: a systematic model and an error model. The systematic model models the effects of the three motivational inputs on the physiological response systems (i.e., Hypotheses 1 and 3) and the lagged feedback effects of the physiological system (i.e., the major origin of the dynamics of the system that moderates and cumulates the motivational input effects, expressed in Hypotheses 2.1 and 2.2). This is the focus of this study. To accurately estimate the parameters for the systematic model, correlations between errors should be modeled and removed; and in this study, an autoregressive model is used for this purpose. The formal equation of the heart rate (HR) model is given below to serve as an example for the four physiological models. Description and rationales for the model are explained immediately following the equation under three subtitles—*the lagged feedback effects of the physiological systems*, *the delayed effects of motivational inputs*, and *the error*.

$$\begin{aligned}H(t) = {} & a_{1\text{h}}H(t-1) + a_{2\text{h}}H(t-2) + b_{0\text{h}} + b_{1\text{h}}A(t-d_\text{h}) + b_{2\text{h}}P(t-d_\text{h}) \\ & + b_{3\text{h}}N(t-d_\text{h}) + b_{4\text{h}}A^2(t-d_\text{h}) + b_{5\text{h}}P^2(t-d_\text{h}) + b_{6\text{h}}N^2(t-d_\text{h}) \\ & + b_{7\text{h}}A(t-d_\text{h})P(t-d_\text{h}) + b_{8\text{h}}A(t-d_\text{h})N(t-d_\text{h}) \\ & + b_{9\text{h}}P(t-d_\text{h})N(t-d_\text{h}) + e_\text{h}.\end{aligned}$$

The lagged feedback effects of the physiological systems

The term $H(t)$ on the left-hand side of the equation is what we are trying to predict, HR at time point t. The first two terms on the right-hand side of the equation, $a_{1\text{h}}H(t-1)$ and $a_{2\text{h}}H(t-1)$, are the first- and second-order lagged feedback terms: $H(t-1)$ and $H(t-2)$ are HR at time points $t-1$ and $t-2$, and their coefficients are $a_{1\text{h}}$ and $a_{2\text{h}}$. These are critical for explaining the time course of the system's response or output to a motivational input.

In a dynamic system, the output of the system depends on several factors: first, the size and duration of the input effect, as the reader might expect; second, the lagged feedback effect/coefficient. The same input can produce dramatically different outputs simply by changing the lagged feedback coefficient of the system which determines the speed, strength, and duration of the output (Boker & Wenger, 2007; Chatfield, 1999; Harvey, 1990; Warren, 2006). A major strength of the proposed DMA model is that it detangles, measures, and tests the input and the feedback effects (i.e., the two components of the systematic model). This is different from conventional static analyses, which aggregate the input and feedback effects, and sometimes mistakenly regard the aggregated effect as the actual input/stimulus effect. In this article, the aggregated effect will be referred to as the "total" effect to differentiate it from the actual input effects (for a MATLAB simulation that demonstrates the importance of the feedback effects in a dynamic system, see http://wongzheng.web.officelive.com/dynamics.aspx).

The delayed effects of motivational inputs

The remaining terms in the HR model with coefficients symbolized by *b*s represent the causal effects of the motivational inputs on HR. This looks very much like a regression equation on its face, but the effects generated by this model do not behave like a regression model. As explained above, this is because the total effects generated by this model include the dynamic response to input effects caused by the feedback factors, $a_{1\text{h}}H(t-1)$ and $a_{2\text{h}}H(t-2)$. Based on a review of the literature, the proposed input effects include all the possibly interesting theoretical effects, including (a) main linear effects of the three motivational inputs (e.g., Ravaja, 2004)—arousing content $b_{1\text{h}}A(t-d_\text{h})$, positivity $b_{2\text{h}}P(t-d_\text{h})$, and negativity $b_{3\text{h}}N(t-d_\text{h})$; (b) their quadratic main effects (e.g., A. Lang, 2006a, 2006b)—$b_{4\text{h}}A^2(t-d_\text{h})$, $b_{5\text{h}}P^2(t-d_\text{h})$, and $b_{6\text{h}}N^2(t-d_\text{h})$; and (c) their two-way linear-by-linear interactions (e.g., Cacioppo et al., 1999; Wang & A. Lang, 2006)—$b_{7\text{h}}A(t-d_\text{h})P(t-d_\text{h})$, $b_{8\text{h}}A(t-d_\text{h})N(t-d_\text{h})$, and $b_{9\text{h}}P(t-d_\text{h})N(t-d_\text{h})$ (Hypothesis 4).

Note that the input effects are delayed by a common amount d_h. It represents the hypothesized time lag for the physiological systems to respond to the motivational inputs from the media content, as proposed in Hypothesis 3. This time delay will be estimated from the data.

Lastly, in the HR model, there is also an intercept parameter, b_{0h}. Generally, for dynamic models, the intercept is meaningful as it can change the dynamic output curve. In this case, however, detrending the data eliminated the intercept effect in most of the data series. This is appropriate because this study focuses on explaining the causal effects of the motivational inputs on the physiological systems and not on modeling simple changes in the physiological systems over time (such as habituation or adaptation).

The error

Finally, the model includes an error term, e_h. In time series modeling, the error in data also requires a dynamic model because there are statistical dependencies in the error across time. If the autocorrelated error is not removed from the total variance, the systematic model cannot be estimated correctly. Here, an autoregressive error model, AR(p), was used to model the autocorrelated residuals, where p is the highest order of the autoregressive terms. It was chosen for its flexibility and mathematical simplicity. Two-model comparison criteria were used to search for the best AR(p) error model: the Bayesian information criterion and the statistical significance of parameters for each lagged error term in competing models. An AR(5) model was found to be sufficient to capture most of the dependence in the over-time residuals—that is, the error model includes lags 1–5.

The equations for the other three physiological variables follow the same form but the value of the parameters are estimated separately for each variable. This allows the models to accommodate the undoubtedly different feedback effects and time courses of the different physiological systems.

Hypothesized dynamic model of channel choice behavior

A somewhat different model is proposed for channel-changing behavior. Channel choice is viewed as a function of interest (I) in the channel which is theorized to be a function of the motivational inputs of that channel. The equation below shows the hypothesized model for interest as a function of the motivational inputs, with $A(t)$ representing the arousing content input at time t, $P(t)$, the positivity input at time t, and $N(t)$, the negativity input at time t.

$$\begin{aligned} I(t) = {} & b_0 + b_1 A(t-d) + b_2 P(t-d) + b_3 N(t-d) \\ & + b_4 A^2(t-d) + b_5 P^2(t-d) + b_6 N^2(t-d) + b_7 A(t-d)P(t-d) \\ & + b_8 A(t-d)N(t-d) + b_9 P(t-d)N(t-d) + e. \end{aligned}$$

Like the physiological response models, this model includes estimates of the linear and quadratic components of the main effects of the motivational inputs as well as their linear interactions. Also, it includes the time delay d. The rationales for including these terms are similar to those proposed for the physiological models. In addition, considering the explorative nature of this modeling effort and the focus on motivational input effects, we included these terms so that we could compare findings across all the dependent variables. Note that a decision was made to keep this model simpler by not including the feedback terms included in the physiological models. Although previous viewing experience influences current viewing experience (e.g., Wang & A. Lang, 2006), the binary choice (to switch vs. not to switch) in this experiment was expected to be primarily influenced by the content being viewed at a given moment.

The next step is to model how interest influences channel choice. The probabilities of the choices (e.g., stay on a channel or switch) are bounded by zero and one, and the probability of choosing an option (e.g., stay) has been empirically found to be an increasing S-shaped function of the strength of the option (i.e., interest in the channel) (e.g., Thurstone, 1927). Therefore, the relationship between interest and channel choice must be nonlinear. Let $S(t) = 1$ if the person stays and $S(t) = 0$ if the person switches at time t. Then, theoretically, this probability should be determined by the motivational inputs through the interest function. Also, a time lag between the motivational inputs and the choice behavior output should be considered. These lead to

$$\Pr(S(t) = 1) = G(I(t - k)),$$

where G is an increasing function bounded by zero and one and k is the time lag. For each participant, based on his or her own data, the best fitting time lag was selected from 11 competing models (using lags from 0 to 10).

The probability function G, which is also called the link function in the generalized linear model, is a logistic function (Hosmer & Stanley, 1989; Kleinbaum, 1994).

$$G(I) = \frac{1}{1 + \exp(-I)} = \frac{\exp(I)}{1 + \exp(I)}.$$

It is chosen here because it is the most commonly used and empirically supported model for choice data (e.g., Hosmer & Stanley, 1989; Kleinbaum, 1994; McFadden, 1986; Sood & Tellis, 2005), and highly efficient programs are available in statistical packages for estimating the model parameters. In particular, we used PROC LOGISTIC in the SAS 9.1.3 statistical package, and we chose the maximum likelihood method for parameter estimation. Note that by default, the PROC LOGISTIC procedure in SAS models the probability of response levels with lower ordered value. That is, in our case, the PROC LOGISTIC procedure predicts the probability of $S(t) = 0$ (switching channels at time t) as we defined earlier.

Method

Pretest and stimuli

Five 5-minute movie clips in each of the six emotional categories created by a Valence (positive, negative) × Arousing Content (arousing, moderately arousing, and calm) factorial design were selected for the pretest. In total, 125 undergraduate students (46.4% male, 76.8% White) with an average age of 20.44 ($SD = 0.12$) viewed and rated the clips using the continuous response measurement (CRM; Biocca, Prabu, & West, 1994) as implemented in MediaLab (Jarvis, 2004). The MediaLab program recorded a respondent's rating 10 times per second and then averaged these values for each second of each 5-minute clip. The rating scale appeared on screen as a 0–100 scale and was automatically converted by MediaLab into a scale ranging from 0 to 2, precise to the hundredth. After viewing each clip, participants also rated how positive, negative, and aroused the clip made them feel on a scale ranging from 1 (*not at all*) to 9 (*very much*).

Each participant viewed and rated 15 randomly assigned and randomly ordered clips. Across participants, all 30 clips were rated continuously on three scales: (a) how aroused do you feel? (the arousing content scale); (b) how positive do you feel? (the positivity scale); and (c) how negative do you feel? (the negativity scale). Each participant watched a given clip once and rated that clip on only one of the three CRM scales. The clips and scales were randomly assigned to participants in such a way that each participant watched two to three clips in each emotional category, rated five clips on each of the three CRM scales, and each clip was rated on all the three CRM scales by a similar number of people.

Based on the average summative ratings for the clips, the final 24 messages were selected as follows. The 12 clips that were rated highest on the positivity scale (Ms > 5) and stayed below 3 on the negativity scale (Ms < 3) were selected as positive clips; the 12 that were rated highest on negativity (Ms > 5) but stayed below 3 on positivity (Ms < 3) were defined as negative clips. Then, within valence categories, the 12 clips were ranked on arousing content and divided into three levels (arousing, moderately arousing, and calm), with four in each level. A manipulation check confirmed that arousing content levels, positivity, and negativity were manipulated successfully (ps $< .001$ and Ms in the expected direction).

After the final 24 clips were selected, CRM data series were processed for each clip to serve as dynamic motivational inputs for the DMA models. The median of CRM ratings at each time point was selected as motivational input for that time point. Finally, to test the reliability of CRM ratings, one CRM data point was randomly selected from every 25 seconds of each clip, generating 12 rating points per clip. Based on the 12 rating items, Cronbach's α was computed for each rating on each clip among the participants. The Cronbach's α indicated that the CRM ratings were reliable ($M_\alpha = .94$, $SD_\alpha = .03$).

Experiment design

In the main experiment, participants watched television for 30 minutes. The television had four available channels and participants were instructed to watch whatever they would like to on the channels. They were informed that they could change channels at will using a remote control and also practiced how to use the remote. In total, 6 of the 24 selected stimuli from the pretest were assigned to each channel, and they were edited together to form a coherent viewing session of 30 minutes (5 minutes $\times$ 6 clips). There were three different viewing orders. Within each viewing order, there were four different orders of presentation of the six clips on each of the four channels. The within and between channel orders were designed to counterbalance the position of clips with different valence and arousing content.

Dependent variables

Zygomatic and corrugator electromyography

These are conceptualized as indices of positive and negative emotional responses which result from viewers' appetitive and aversive activations respectively (Ito, Chiao, Devine, Lorig, & Cacioppo, 2006; Larsen et al., 2003). The zygomaticus major muscle group is located under the cheek and is involved in smiling. The corrugator supercilii muscle group is located above each eyebrow and is involved in frowning. For all the physiological measures in this study, an Ampac 386 computer with a LabMaster AD/DA board, and Coulbourn S-series modular components were used to collect the data. VPM 12.1 (Cook, 2000) was used to control the data collection process. For zygomatic and corrugator electromyography, muscle potentials were sampled at 20 Hz.

Skin conductance level

This is a measure of sympathetic nervous system activation that is theorized to be related to motivational activation (M. Bradley & P. Lang, 2000). Higher skin conductance level is attributed to increased activation in the sympathetic nervous system which indexes higher physiological arousal and suggests more intense motivational activation. The data were collected from the palm of the nondominant hand sampled at 20 Hz.

HR

During resource allocation to external stimuli such as television messages, activation of the parasympathetic nervous system increases, resulting in measurable decreases in HR (A. Lang, 1994). Slower HR reflects greater cognitive effort. The intervals between beats were recorded and then converted to beats per minute.

Channel changing

Channel changing is viewed as choice behavior which is a function of interest in the motivational content of television programming. VPM recorded both the time at which a channel change was made and the channel options (corresponding to certain motivational content). Then, a MATLAB program was created to generate the 1800-second long time series with one data point per second for each channel, dummy-coding 1 for a time point if the channel was watched at that time and 0 if not.

Procedures and participants

Participants completed the 1.5-hour experiment individually. After the experimenter demonstrated how to use the television remote control and attached electrodes to the participant, the experimenter left the room and closed the door to provide privacy during viewing. Then, the four 30-minute stimulus tapes were simultaneously played on a wired set of four videocassette recorders (VCRs) outside the experiment room. The participant watched the content on a 25-inch television that was connected to the VCRs. While viewing, the participant could use the remote control to change channels at any time. Participants' physiological responses and channel-changing behaviors were collected continuously during viewing. In total, data were obtained from 67 participants. The average age was 21.13 ($SD = 1.28$, range 18–25); 41 (61.2%) were males; and the majority were White (80.3%), followed by Asian (8.5%), African American (4.2%), and Hispanic (2.8%).

Modeling analysis and results

Time series data sets

For the dependent variables, time series were created for each participant using four physiological measures and channel choice behavior obtained at a rate of one observation per second for 1800 seconds. The physiological data were initially processed by removing linear trends of time using the general linear model procedure in SAS (PROC GLM) for each variable and each person. This detrending process is needed because when using time (1800 time points) as a predictor, linear regression tests found that time had a significant effect on each of the physiological variables (ps $<$ .001); but this general, nonstimulus-specific trend in the physiological responses is not the focus of this study. After detrending, to put the physiological variables onto the same scale for easier interpretation of the model parameters, the data were transformed to standardized scores for each variable for each person.

To create the independent variables, three 1800-second time series were created using the medians for arousing content, positivity, and negativity CRM data obtained in the pretest. Next, because participants were in control of their channel-changing behavior and therefore each participant viewed different video content at different times, three time series were created for each participant based on their personal channel viewing. A MATLAB program was created to align the CRM ratings in time (i.e., second by second) with the video content actually watched by each participant. For each participant, this data-matching procedure produced a series of 1800 seconds of ratings for the three motivational inputs over time based on the person's actual viewing experience. Thus, for each participant, we obtained a data matrix consisting of eight columns of variables (three inputs and five outputs) and 1800 rows of observations across time. This data set was used to estimate the parameters of the proposed DMA models (for a visual representation of the raw data of a single participant's actual inputs and outputs, http://wongzheng.web.officelive.com/dynamics.aspx).

Model fitting and model performance

For each participant, the proposed four physiological models were estimated using maximum likelihood methods and PROC AUTOREG in the SAS software. To search for the best delay lags for the motivational input effects, for each model and for

Table 1 Descriptive Statistics of the Regression R^2s of the Physiological Models ($N = 67$)

The Model	Minimum	Maximum	Mean	*SD*
HR	0.42	0.95	0.74	0.11
Skin conductance	0.81	0.99	0.96	0.04
Corrugator EMG	0.13	0.97	0.76	0.16
Zygomatic EMG	0.36	0.97	0.81	0.15

Note: HR = heart rate; EMG = electromyography.

each person, 11 lagged models (using lags from 0 to 10) were estimated. Based on the regression R^2 predicted by the systematic model, the best lag model was selected for each physiological model for each individual. The average regression R^2 across all participants' data sets is relatively large. The descriptive statistics are shown in Table 1. On average, across the 67 participants' individual data sets, the dynamic models account for at least 74% of variance in the time series of the corresponding physiological variable.

For the channel choice model, first, a chi-squared test was performed on the hypothesized full model (with 10 parameters) compared with a restricted null model (without parameters associated with the motivational input effects). The Bayesian information criterion was used to evaluate the complete model compared with the null model because its evaluation on models is based on both goodness of fit and model complexity (Wasserman, 2000). For all the participants, the full model exceeded the null model. Then, percentage of concordance (the percentage of correct predictions across the 1800 time points) for each participant was used to examine how well a model can predict compared with the real data. For each participant, the best fitting lag model was selected from the 11 competing models with 0–10 lags. Overall, the percentage of concordance for all the participants had a mean of 73.40 ($SD = 7.37$, range 61.00–94.30), suggesting that on average, the selected model can predict 73.40% of data points for participants. In summary, the goodness of fit of the four physiological models and the channel choice model supports Hypothesis 1.

Effects of motivational inputs

After model fitting for each model for each viewer, we obtained a set of 12 systematic model parameters for each physiological variable from the best fit lag model and 10 for the channel choice model. First, multivariate analysis of variance (MANOVA) was used to test the significance of the motivational effects on the physiological responses and channel choice (i.e., parameters for A, P, N, A × P, A × N, P × N, A^2, P^2, and N^2). Each of the motivational input effects, as estimated by the model parameters, was tested. For example, to test the linear effect of arousing content (i.e., the parameter for A), each individual's parameters for A from all five of the models were entered into the MANOVA test simultaneously.

Hotelling's T^2 was significant for the main effect of arousing content (both the linear and quadratic components), its interactions with positivity and with negativity, and the quadratic component of the positivity main effect. For parameters with significant Hotelling's T^2, Student's t tests were performed on each parameter for each model to determine: (a) whether the mean (across participants) of each parameter differs significantly from zero, and (b) the sign and size of each parameter. If the mean of a model parameter is significantly different from zero, this suggests that the effect associated with the model parameter is significant. The sign and size of the parameter tell us about the size and direction of the effect estimated by each parameter. The motivational effects on physiological variables are summarized in Table 2 and those on channel choice are summarized in Table 3. For easier comparison across parameters, F values converted from t scores are reported.

Lagged responses of physiological systems

Next, we examined the feedback parameters that determine how quickly the motivational inputs activate or deactivate the physiological systems. Specifically, the first step is to determine how the physiological response feeds back on and influences itself. t tests were conducted on the two lagged feedback parameters in each model to determine the significance, direction, and size of the feedback effects. The results are reported in Table 2. Supporting Hypotheses 2.1 and 2.2, all four physiological systems have significant lag one and lag two feedback effects. As explained earlier, this means that the asymptote for a system's responses to motivational inputs depends on not only the size and duration of the input effect but also the system's feedback. In addition, it is worth noting that these lagged feedback effects occur even after the noise in the physiological time series data has been modeled with an autoregressive (lag 5) model as described earlier. Therefore, we can exclude the possibility that these feedback effects are due to autocorrelated error in the data series.

Delayed motivational input effects

Next, to determine how quickly the motivational inputs reach and produce an effect on the physiological systems, the number of lags in the best-fit lagged model for each participant and each model was examined. Recall that the model for each physiological response uses the motivational inputs that occurred at a time d seconds earlier to predict the current physiological response (Hypothesis 3). The delay d is the lag parameter. Also recall that during our parameter estimation for each physiological model, we compared each model with 11 different lags (0–10 lags/seconds) and selected the best fit for each participant. The results support Hypothesis 3. Indeed, there were time lags between the onset of the motivational inputs and the physiological responses. The mean for the only unimodal distribution, HR lags, is 5.37 ($SD = 2.99$). For skin conductance level, the lags are bimodally distributed ($M = 5.25$, $SD = 3.15$), with the dominant mode being 7 ($n = 10$) and another peak at 2 ($n = 8$). For corrugator and zygomatic activities, the lags are also bimodal ($M = 4.49$, $SD = 3.31$ and $M = 4.94$, $SD = 3.34$, respectively), with modes at 0 ($n = 10$) and 5 ($n = 9$) for corrugator activity and 4 ($n = 8$) and 10 ($n = 8$) for zygomatic activity. These distribution patterns suggest that participants showed

Table 2 The Means, F Values, and Effect Size of the Parameters in the Dynamic Physiological Models ($N = 67$)

	The HR Model			The Skin Conductance Level Model			The Corrugator EMG Model			The Zygomatic EMG Model		
Parameters of Effects	*M* (*SD*)	*F*	ε^2	*M* (*SD*)	*F*	ε^2	*M* (*SD*)	*F*	ε^2	*M* (*SD*)	*F*	ε^2
Lag 1	1.00 (0.03)	884.51*	0.93	1.18 (0.04)	1112.12*	0.94	0.59 (0.09)	46.59*	0.41	0.99 (0.04)	546.86*	0.89
Lag 2	−0.26 (0.04)	38.26*	0.36	−0.20 (0.03)	35.77*	0.35	−0.08 (0.04)	4.26*	0.06	−0.16 (0.03)	23.02*	0.26
A	−0.06 (0.03)	4.99*	0.07	0.01 (0.01)	0.89	0.01	−0.14 (0.05)	7.35*	0.1	−0.14 (0.03)	22.20*	0.25
A × P	−0.05 (0.03)	3.40†	0.05	−0.01 (0.01)	1.31	0.02	−0.02 (0.04)	0.34	0.01	0.08 (0.04)	4.00*	0.06
A × N	−0.03 (0.03)	0.93	0.01	−0.01 (0.01)	1	0.01	−0.01 (0.03)	0.23	0.003	−0.07 (0.04)	2.68†	0.04
A^2	0.05 (0.02)	5.23*	0.07	0.003 (0.01)	0.13	0.002	0.06 (0.03)	4.97*	0.07	0.06 (0.02)	6.65*	0.09
P^2	0.05 (0.02)	4.98*	0.07	0.01 (0.01)	1.75	0.03	0.02 (0.04)	0.17	0.002	−0.06 (0.02)	3.08†	0.04

Note: HR = heart rate; EMG = electromyography.
$^*p < .05$. $^\dagger p < .10$.

Table 3 The Means and the *F* Values of the Parameters in the Channel-Changing Behavior Model($N = 67$)

Parameters of Effects	Mean (*SD*)	*F* Value	Effect Size ε^2
A	−2.09 (0.74)	7.92*	0.11
A × P	0.53 (0.72)	0.55	0.008
A × N	1.56 (0.60)	6.80*	0.09
A^2	0.79 (0.49)	2.63†	0.04
P^2	−0.81 (0.98)	0.68	0.01

*$p < .05$. †$p < .10$.

similar central tendency in HR changes as a function of motivational inputs, but the bimodal distributions for the other measures suggest that there may be faster and slower response groups for these physiological systems (for plots of the distributions of lags for each physiological response across participants, see http://wongzheng.web.officelive.com/dynamics.aspx).

Putting it all together: Dynamic effects of motivational inputs across time

In this final analysis, we put together all the reported effects and examine how each physiological system responds dynamically to some selected motivational inputs *across time*. This helps examine the integrated, "total" effects of the motivational inputs on each system. In this section, the actual parameters for each physiological system estimated from the real data are entered in the hypothesized models to illustrate how the systems work in general. Following a common time series analysis strategy, eight different combinations of the three motivational inputs, being set to either "on" or "off" during a specific time period, are selected to demonstrate the effects of arousing content, positivity, and negativity on the dynamic system. They are (a) all three inputs are off, (b) only arousing content is on, (c) only positivity is on, (d) only negativity is on, (e) arousing content and positivity are on but negativity is off, (f) arousing content and negativity are on but positivity is off, (g) positivity and negativity are on but arousing content is off, and (8) all three inputs are on. For the last input condition, please note that this condition is not to test or demonstrate a three-way interaction of the motivational inputs; instead, this condition examines the integrated effect when all inputs are turned on—that is, the integrated effect from all the hypothesized effect terms in the model. Then, we can observe, for each of the eight conditions, how each system responds. This is one of the advantages of mathematic modeling where the information of the participants' responses is extracted by the estimated model parameters, and our analysis and understanding does not have to rely solely on the actual observation of human data.

For ease of interpretation, all the magnitudes of the three inputs are kept at .6. This value is selected because it is moderate, which puts all eight combinations of the inputs within the actual range of the experimental stimuli. Here, the use of a step input (from zero to a fixed level) is the most commonly used analytic tool for

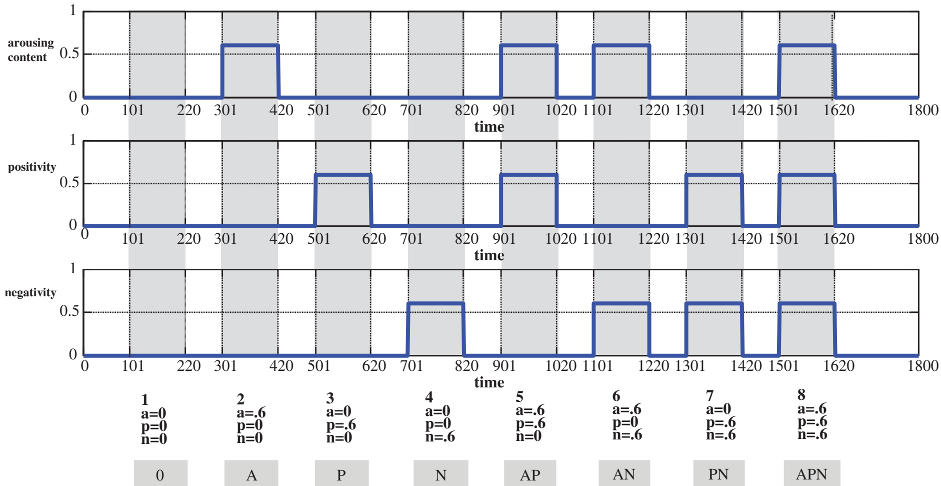

Figure 1 Eight conditions of motivational inputs with arousing content, positivity, and negativity being on and off during different time periods (input magnitude = .6).

analyzing the dynamic effects of inputs across time (Luenberger, 1979). The zero setting allows the system to return to its natural baseline after each input is turned on, allowing the activation and decay of an input combination to be examined clearly. Otherwise, it would be difficult to decipher its effect in the figures. Figure 1 shows what the inputs look like. The step input duration is 120 seconds each and the zero setting is 80 seconds each. For convenience of discussion, the eight conditions are labeled as (1) 0, (2) A, (3) P, (4) N, (5) AP, (6) AN, (7) PN, and (8) APN. These same eight input conditions are used to demonstrate all four dynamic models of physiological responses across time, as shown in Figures 2a–d. For each figure, these eight input conditions are always presented in text at the bottom of the figure with the corresponding step input durations highlighted in gray.

As shown in Figure 2a, the HR pattern predicted by the dynamic model is very much in line with the large amount of previous data measuring HR in response to emotional media messages. That is, nonarousing (or calm) positive and negative messages elicit only a slight change in HR. When arousing content is added to either positive or negative messages, HR decelerates strongly (e.g., Öhman, Hamm, & Hugdahl, 2000). Interestingly, from previous research, little is known about how coactive messages (containing both positive and negative content simultaneously) influence HR, and this coactive condition was not intended to be manipulated and tested in this study; however, as shown in Figure 2a, this dynamic model clearly predicts a HR acceleration if the coactive messages are calm (Condition PN) and a HR deceleration if they are arousing (Condition APN). Future research can test this prediction.

Figure 2b shows the dynamic changes in the skin conductance level. Arousing content causes a large rise in skin conductance level (Condition A), which is consistent with previous findings. It is interesting to see that when arousing content is set

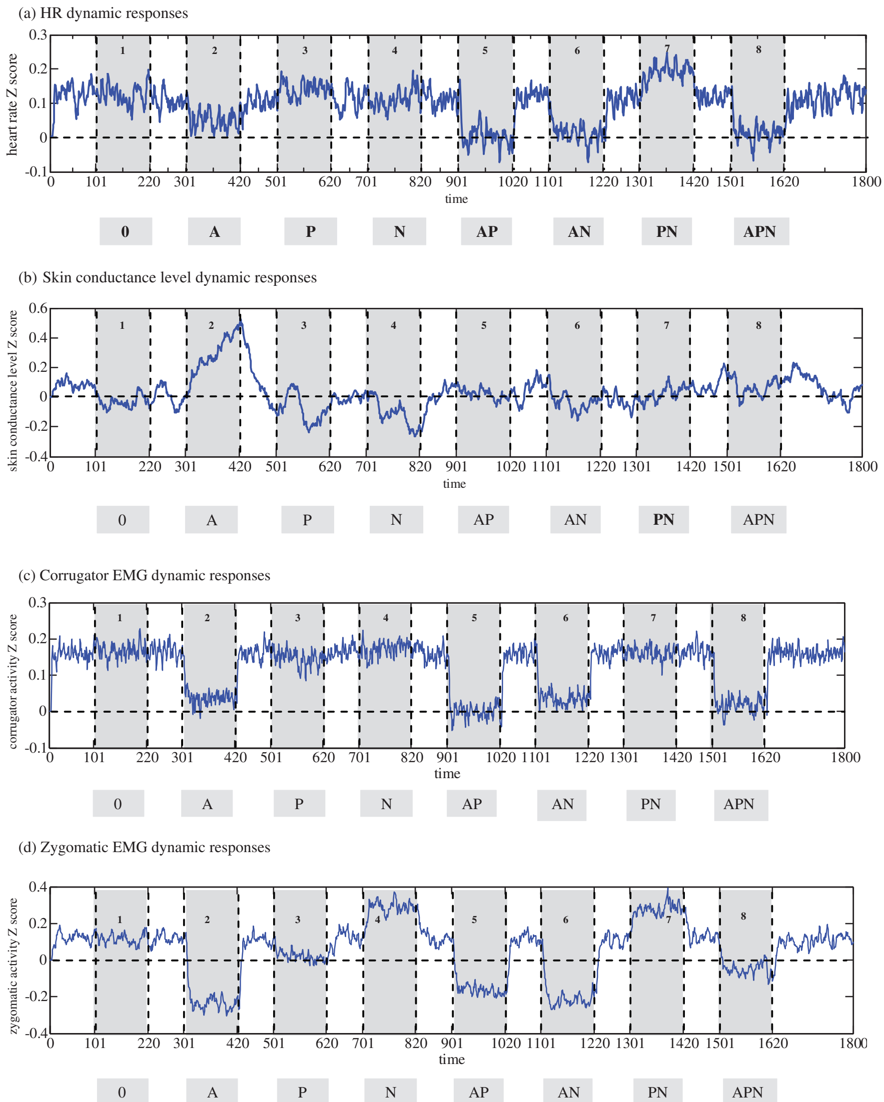

Figure 2 Dynamic physiological responses to motivational inputs with arousing content, positivity, and negativity being on and off during different time periods (input magnitude $= .6$), using averaged model parameters across all participants ($N = 67$). The predicted physiological data are scaled with respect to the averaged actual physiological data Z scores of all participants. (a) HR dynamic responses. (b) Skin conductance level dynamic responses. (c) Corrugator EMG dynamic responses. (d) Zygomatic EMG dynamic responses.

to be off, a slight input of positivity or negativity (Conditions P and N) causes a skin conductance level decrease. Although previous research did not control the level of arousing content to be exactly zero, which seems to be practically impossible in experiments involving real-world media stimuli, a large amount of research has examined calm positive and calm negative messages. Those empirical studies show exactly the same response pattern as predicted by the model: Skin conductance decreases across the course of calm messages. Unexpectedly, however, when arousing content is on, along with either positivity or negativity (Conditions AP and AN), there is almost no change in skin conductance levels. This is contrary to a large amount of published empirical research and needs to be considered. Finally, for the seldom examined coactive conditions (Conditions PN and APN), the model predicts small changes in skin conductance level, especially when the content is not arousing. In general, this model seems to be rather "nonresponsive" toward the various motivational input conditions except for the condition of arousing content being turned on.

As Figure 2c illustrates, a clear pattern appears for corrugator responses to motivational inputs: the presence of arousing content always reduces corrugator activity greatly, especially when positivity is also presented. It is interesting to note that when the input is positive but not arousing (Conditions P and PN), corrugator activity does not show much change.

Figure 2d shows a surprising pattern of zygomatic responses with increased zygomatic activity in response to negativity and nonarousing coactive content but decreased zygomatic response toward arousing content or its copresentation with positivity or negativity.

Discussion

In general, many of the findings of the dynamic time series modeling approach, particularly the integrated effects of motivational inputs and system feedback, are consistent with previous literature using traditional static methods. This DMA mathematical implementation, however, makes three theoretical contributions that extend previous work. First, it examines effects of motivational inputs during information processing *across time*; second, it explores the dynamic, cumulative effects of motivational inputs as determined by the feedback effects of the physiological systems; third, it investigates channel choice behavior as a function of motivational activation and connects the behavioral outcome with psychophysiological responses.

Effects of message arousing content, positivity, and negativity across time

Cacioppo and colleagues' (1999) dual system model of emotion, and its application and development in media research by the LC4MP, strongly supports the separability of positivity and negativity. This study decomposed valence into separate positive and negative affective components and *formally* examined their effects and their interactions with arousing content across time. Consistent with previous research, positivity and negativity were found to elicit appetitive or aversive responses and arousing content was found to determine the intensity of the response.

The quadratic effect of arousing content was found to be robust. It was significant and positive on HR, corrugator and zygomatic activities, and also on channel-changing behavior—which means that the U shape of the quadratic trend opens upwards. These results suggest that as arousing content increases, cognitive effort increases (indicated by an initial decrease in HR), which may result in less facial expression and also a lower probability of changing channels. However, when the message content becomes even more arousing, HR accelerates (in our data, at a value of about .7 on the 0–2 rating scale for arousing content), leading to increased smiling or frowning (for both, at about 1.2 on the 0–2 scales), which is coupled with an increase in the probability of changing channels when the content is negative (around 1.3 on the 0–2 scale). This HR acceleration during very arousing messages is probably due to behavioral preparation to approach when messages are extremely pleasant and arousing or to withdraw when messages are extremely unpleasant and arousing. Because cardiac activity is simultaneously controlled by the sympathetic nervous system (SNS, dominant during mobilization) and the parasympathetic nervous system (PNS, dominant during external attention), this HR acceleration may result from the SNS activation dominating the PNS activation at the high levels of motivational activation (Andreassi, 1995). It is worth pointing out that these findings are consistent with research concerning the "intake–rejection" hypothesis (e.g., Lacey, 1967) and the cardiac–somatic concept (Obrist, Webb, Sutterer, & Howard, 1970), which argue that cardiac deceleration facilitates information intake from the external environment and cardiac acceleration rejects the incoming information to avoid disruption of the current cognitive activity (e.g., imagination) or to facilitate preparation for behavioral responses (e.g., fight or flight). Previous empirical research guided by LC4MP has largely supported those hypotheses using media message stimuli. This study adds more support to these hypotheses. It provides stronger evidence of the quadratic effect of arousing content in the sense that the estimated effect is per time unit (per second, in this case) so that it is not confounded by stimulus durations and the system feedback effects. The findings and the dynamic approach here can generate insights to provide a better understanding of the role of arousing content, particularly its optimal level, on advertising effectiveness (e.g., Pavelchak, Antil, & Munch, 1988) and learning from the media (e.g., Grabe, A. Lang, Zhou, & Bolls, 2000).

Other findings of interest relate to the coactivation condition. Little empirical data exist on how the physiological systems respond to coactivation of the two motivation systems. The results produced by this model may be used to predict and test the effects of coactivation on physiological responses in future studies. However, caution should be used when doing so because the message stimuli in this study were selected to be fairly unidimensional (i.e., high negativity and low positivity or vice versa). Indeed, the Pearson correlation r between the CRM ratings of positivity and negativity for these messages varies from $-.79$ to .23, suggesting a fairly low level of coactivation. Any model parameter estimated using a single data set is restricted to the data as well as the testing context, and researchers should be cautious not to overgeneralize the findings. Nonetheless, it is still worth noting that in this study, the presence of coactivation increases HR when the content is very calm but decreases HR when the content is slightly arousing. More importantly, this study demonstrates the utility of a dynamic modeling approach in understanding a large range of interesting media uses and effects phenomena concerning ''coactivation,'' such as enjoyment of aversive media content (e.g., Oliver, 1993).

Lagged feedback effects of the physiological systems

Supporting the DMA prediction, our findings show that motivational effects do not appear and disappear instantaneously with the onset or offset of motivational inputs. The significant lagged feedback effects indicate that motivational inputs take time to change and grow toward their equilibrium state. In other words, the feedback effects determine the final level of growth and the cumulative effect produced by a motivational input.

This also means that the duration of the inputs is critical because the size of the observed motivational effects always depends on where the system is on the effect evolution trajectory and how long it has been there. It is probably worthy of notice that if researchers do not use the same durations in their stimulus presentations, they may not be able to replicate each others' findings even if the experimental designs are very similar. In static analysis, this difference in input effects caused by stimulus presentation duration is easily overlooked because only the factor manipulation levels are considered. In time series modeling, however, this input duration difference becomes critical and is examined. In addition, this dynamic approach may help us better understand cumulative, long-term effects of media and extended exposure to certain media content, such as desensitization to aggressive media content (e.g., Linz, Donnerstein, & Penrod, 1984; Thomas, 1982).

Limitations and implications

Several limitations of this study need to be noted. First, this study found that skin conductance level was quite nonresponsive. This might result from the quick habituation of skin conductance responses (Andreassi, 1995) and the long viewing time in this experiment. Another possibility is that the structural complexity and information density of stimuli were not controlled in this study, which can affect physiological responses (e.g., Potter, A. Lang, & Bolls, 1998). Future studies should either control or manipulate these factors.

Second, zygomatic activity did not conform to the pattern of results seen in the literature. It sometimes increased with increasing negativity and decreased with increasing positivity, which is the reverse of the expectation. This may be partially caused by the fact that a great deal of the negative media content used in this study is designed to be entertaining (A. Lang, 2000). In addition, it might be explained by the findings in some recent studies that ''a smile is a frown turned upside down'' (Ansfield, 2007, p. 763). These studies found that people smile when distressed because of their need for emotional self-regulation and self-presentation. Further replications are needed to see whether the opposite response patterns of zygomatic activity shown in this study are indeed replicable.

Third, for channel-changing behavior, because this study focused on examining how it was affected by motivational content inputs, the channel choice model did not include any feedback term to test whether the current channel choice was affected by previous choices. However, the emotional context created by television programs has been found to affect subsequent advertising processing (e.g., Wang & A. Lang, 2006), and attention during television viewing has been found to include an inertial component (e.g., Anderson, Choi, & Lorch, 1987). These findings suggest that previous channel choices may influence current choice. Future research should examine whether the current channel choice is conditioned on previous choices, and if so, how this conditioning interacts with different media content features.

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