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Multimodal Physiological Responses Predict Advertisement Effectiveness

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ABSTRACT

Advertising research using biometric measures has long observed a mismatch between physiological responses and psychological outcomes. This study provides new insights using a multimodal approach to analyzing physiological data and testing its relationship with advertisement effectiveness. This study temporally coupled orbicularis oculi (OO) and corrugator supercilii (CORR) activity as an integrated indicator of emotion, whereas coupled heart rate (HR) and skin conductance level (SCL) indicated engagement. In doing so, we identify multimodal physiological dynamics that effectively predict attitude toward and memory about ads. Results showed that the emotional pattern stability, or recurrence, predicted viewers' attitudes and purchase intentions and engagement pattern stability predicted recognition memory. Specifically, participants who experienced a less stable co-active state (high OO and CORR) reported more favorable attitudes and purchase intentions. On the other hand, participants who experienced a more stable high-engagement state (low HR and high SCL) had enhanced brand recognition memory, while more stable uncoupled-engagement state (low HR and low SCL) participants exhibited enhanced visual recognition memory. This study provides theoretical and analytical insights for understanding the previously observed mismatch between physiological responses and outcome measures. The findings enhance our understanding of how physiological processes during ad viewing impact consumer attitude and memory.

Established literature demonstrates the success of biometrics in predicting message effectiveness (Read et al. 2024) and advancing communication theory development (Potter, Ni, and Marlet 2024). In particular, biometric measures from the central and peripheral nervous system predict real-world behavior (Falk, Berkman, and Lieberman 2012; Venkatraman et al. 2015) and cognitive and emotional processes during media use (Lang, Potter, and Bolls 2009). Despite some promising biometric findings, scholars in the fields of communication, marketing, and psychology have long observed a mismatch between (1) media effects on biometric indicators that reflect psychophysiological processes and (2) media effects on psychological outcomes, typically measured by self-reported experiences and feelings. While many theories in message processing and advertising effectiveness conceptualized physiological reactions as the underlying mechanism for various psychological processes and outcomes (e.g., Cacioppo, Tassinary, and Berntson 2007), this *physiological process–psychological outcome* mismatch poses critical challenges for the conditional truth of those theories (Lang 2020), in which results that do not match up with theory predictions may not receive enough attention from the field.

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For instance, the Limited Capacity Model of Motivated Mediated Message Processing (LC4MP, Lang 2006) predicts that highly arousing positive messages should be well remembered compared to other messages such as calm positive and calm negative ones, in that arousing-positive messages elicit greater appetitive system activation, which fosters information intake. However, as concluded in Lang (2020) at the end of her scholarly career, previous findings showed that this is often not the case. This observed mismatch likely stems from studies that based their conclusions on physiological data showing overall increases in motivation system activation and attention when viewing arousing-positive messages; based on the LC4MP, these should produce the best encoding memory, but memory data indicated otherwise (Lang 2020). There is a limitation of the LC4MP counterevidence. When many studies testing the LC4MP or other theories about how message features influence viewing outcomes, a fundamental assumption is that the body—the mediating state—will react to the messages as predicted, lacking robust manipulation checks (Keene, Lang, and Loof 2019; O'Keefe 2003; Thorson, Wicks, and Leshner 2012). Notably, manipulations are often checked via self-report, asking participants to indicate perceived physiological responses. However, self-reports may indicate the manipulation as successful from the subjective experience perspective, whereas physiological data may reveal no actual difference between the predefined message categories, whether on average, consistently over time, or both. The discrepancy between LC4MP predictions and findings highlights the need for more precise manipulation checks, especially testing the mediating state in media effect research.

Another methodological feature may also account for such discrepant findings. Even when multiple physiological signals are simultaneously measured in a study, these signals are often analyzed in separate statistical models and then interpreted collectively in discussion. Moreover, this traditional approach commonly relies on averaging the physiological signals across participants and sometimes also averaged across time. When multiple signals are analyzed individually and averaged over time and across participants, the moment-to-moment relationships between signals are lost, which can lead to misinterpretations. Suppose high engagement with a message does require both increased skin conductance level (SCL, indicative of motivational systems activation) and decreased heart rate (HR, indicative of attention during message viewing) and will lead to better memory outcomes (Lang 2014); to see this effect, one needs to identify time points where both decelerated HR and increased SCL occur at the same time and at the individual level. If decelerated HR and increased SCL occur, but not at the same time, physiological response may not best support the encoding process and recognition memory. Following related calls in neuroscience (Favela 2021), technological advancements (i.e., human sensing) must necessarily be accompanied by analytical and conceptual frameworks that allow for new understandings to emerge.

This paper tests the overarching argument that the physiological process–psychological outcome mismatch is, in part, due to methodological and analytical limitations. We apply a research lens through which dynamic, higher-order states are captured, which we hypothesize can provide improved indicators of consumer attitudes and behaviors, with results also more in line with communication and psychology theory. Rather than dividing multimodal data into unidimensional indices, we examine the time-locked interplay of multiple physiological signals to capture collective physiological patterns that shape ad post-viewing attitudes and memory. Hence, rather than predicting advertising outcomes based on message characteristics, this study directly analyzes physiological patterns and explores their relationship with ad viewing outcome variables.

While our approach is not intended to directly modify existing theories, we believe it supports theoretical development by directly addressing the physiological process–psychological outcome mismatch, which otherwise challenges popular theories like the LC4MP. The work also advances communication literature by forwarding a new analytic approach for understanding multimodal, time-evolving processes, which, as demonstrated in this study, facilitates a testing paradigm that aligns more closely with theoretical assumptions and predictions and thus may be better studied for theory testing.

The Physiological Process–Psychological Outcome Mismatch

For the past four decades, media psychologists have been applying biometric measures to media and communication research (Potter, Ni, and Marlet 2024), forwarding a classic experimental paradigm for understanding how message features influence physiological processes and psychological outcomes (Falk, Cascio, and Coronel 2015). In this paradigm, message features are manipulated to induce participants' psychological

changes. Information processing during message exposure, measured with real-time biometric signals, is viewed as the result of message manipulation as well as the underlying mechanism driving psychological or behavioral outcomes. The logic is that the underlying processes should provide insights into the message effects on outcome variables such as attitude and memory.

Equipped with this experimental paradigm, existing theories have made significant progress in establishing how message features predict neurological and physiological processes across contexts such as advertising, entertainment, and health. Nevertheless, for decades, the mismatch between neurological and physiological processes and participants' viewing outcomes following message exposure remains an unsolved theoretical and methodological issue (see Figure 1 for illustration). Importantly, these mismatches could challenge the validity of using biometric measures to indicate psychological processes due to its many-to-many mapping nature with psychological variables (see Poldrack 2006; Weber et al. 2015). Hence, the attempt to use biometric measures to understand media effects or link to viewing outcomes seems to have fallen short.

The mismatch between physiological processes and psychological outcomes is often an incidental finding reported in studies, rather than the target of investigation. Studies investigating how advertising features influence psychological processes typically collect biometric and self-report/outcome data as dependent variables and analyze them in separate statistical models. This approach often yields apparent disagreement between biometric and self-report/outcome data (e.g., emotional feelings). For example, a series of Lee and colleagues' studies examined how the emotional valence and arousal levels of sports programs influence cognitive and emotional responses during the viewing of subsequent advertisements. While one study found consistent patterns between HR deceleration and memory about viewing content, as expected by the LC4MP (Lee, Potter, and Pedersen 2019), a follow-up study did not observe such consistency (Lee, Potter, and Han 2023). In another study, Lee et al. (2018) investigated sports fans' emotional responses to advertisements as a function of the same variables as tested in the previously mentioned studies. While self-reported attitudes toward the advertisement and brand varied as a function of these variables as expected, physiological measures (orbicularis oculi [OO] and corrugator supercilii [CORR] muscle group activations) reflecting viewers' emotional responses were not significantly affected by these independent variables, in contrast to theoretical predictions. Overall, Potter, Ni, and Marlet (2024) completed a comprehensive qualitative review of 135 articles using biological measures from six major outlets that publish media psychology research. Among the 67 studies reporting both physiological and self-reported results, nearly half revealed inconsistencies, highlighting the prevalence of this disconnection issue.

The long-standing difficulty in linking physiological processes with psychological outcomes has led some researchers to propose alternative approaches. For example, Falk and colleagues (Berkman and Falk 2013; Falk, Berkman, and Lieberman 2012) introduced the "brain-as-predictor" framework, which directly links neurophysiological processes with real-world behaviors. This approach has demonstrated that fMRI data can predict real-world outcomes, such as population-level purchasing behavior and smoking

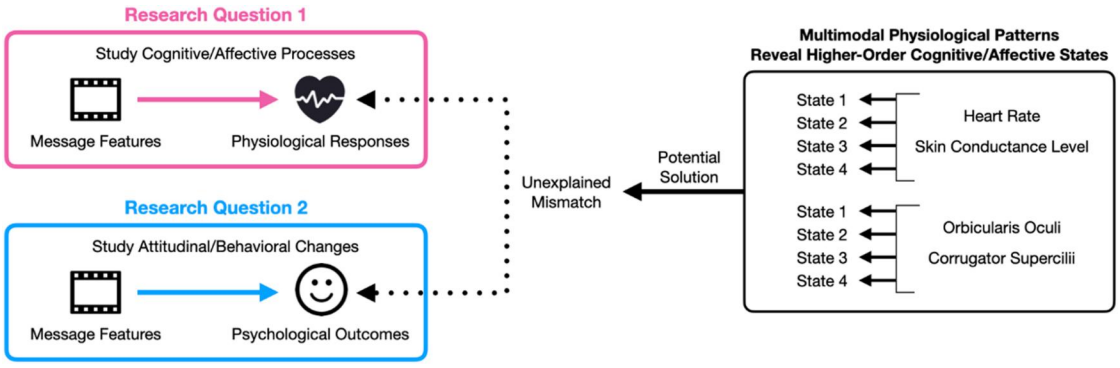

Figure 1. Conceptualization of the current study.

Note. Well-established media effect research has examined the relationship between message features and physiological responses (top left panel) and between message features and psychological outcomes (bottom left panel). The relationship between physiological responses and psychological outcomes, which should align in theory, often shows unexpectedly mismatched patterns. In the current study, we argue that a potential solution to resolve such mismatch is to use multimodal physiological states (right panel) to provide improved resolution in human state estimation and more fruitfully understand linkages with psychological outcomes.

cessation (see Falk, Berkman, and Lieberman 2012), bypassing the traditional reliance on attitudes, memory, or subjective evaluations, which are often used as proxies for real-world outcomes. While this brain-as-predictor framework offers valuable insights into the predictive utility of neurophysiological measures, we argue that the longstanding mismatch between process-based measures and self-reported attitudes and memory outcomes remains an unresolved phenomenon that is worth further exploration. Understanding this mismatch is crucial for bridging the gap between theoretical arguments and empirical observations, thus facilitating theoretical development and enhancing application of biometrics in advertising research.

Forwarding Multimodal Physiological Patterns to Arbitrate the Physiological Process–Psychological Outcome Mismatch

The human body is a complex system consisting of multiple biological subsystems including nervous, cardiovascular, respiratory, endocrine, and muscular, which constantly and dynamically interact with one another to maintain physiological and psychological functioning (Lang 2020). In this way, a physical detail is never responded to with a message detail; instead, the co-occurring and interconnected nature of physiological processes means that the human body responds to messages and other changes in their surroundings in a holistic manner. Bodily responses such as cognitive and emotional responses to environmental changes should be considered together when identifying and referring to a specific psychological state at the moment, forwarding a system-level dynamics approach in understanding human processes and outcome variables (Han et al. under review).

Coupling OO and CORR Activity to Predict Ad Attitudes

While many studies demonstrate the predictive power of emotional content on physiological responses (reflecting one's emotional processes) and self-reported attitudes separately, scholars have always observed a mismatch between these physiological and self-reported psychological effects (refer back to Figure 1). Previous advertising research has primarily studied the emotion-and-attitude relationship within the media effects paradigm (see review in Potter, Ni, and Marlet 2024). The idea is that by manipulating the emotional content of advertisements and testing its effect on physiological responses and/or self-reported attitudes, it would clarify how emotion influences consumer attitudes. The mismatch between emotional responses measured physiologically and self-reported feelings raises the question of how emotional content influences self-reported attitudes and whether physiological responses mediate this relationship. If physiological responses do not reliably correspond to people's experiences, feelings, and decisions, then the value of physiological measurement in advertising is limited. However, if physiological responses and self-reported emotions are significantly related to attitudes, then it is important to understand the nature of their relationships.

The dimensional theory of emotion argues that the valence of emotion, namely positive and negative emotion, is organized by two independent motivational systems: the appetitive system facilitating approach behaviors in response to beneficial stimuli like food and the aversive system facilitating avoidance behaviors in response to potential threats (Bradley et al. 2001). Previous research commonly references OO as indicative of the appetitive motivational system activation and CORR activity as indicative of the aversive motivational system activation; taken together, the two signals reflect positive and negative emotion, respectively (Potter and Bolls 2012). These two signals have traditionally been analyzed in separate statistical models but have always been interpreted collectively. This decision may reflect, in part, arguments that motivational systems operate independently (Cacioppo and Gardner 1999), implying that positive and negative emotions do not always share a reciprocal relationship (i.e., an increase in one does not necessarily mean a decrease in the other) and therefore can be reasonably measured and analyzed separately. While there are instances when separately analyzing the signals are justified, the theory can conversely be interpreted as indicating the importance of understanding of more nuanced relationships among multiple co-occurring and influential emotional states. In this case, the dynamic relationship between the OO and CORR signals has the potential to reveal higher-order emotional states relevant to understanding advertisement response (e.g., where people's experience of high OO may vary based on the CORR level).

The examination of higher-order emotional states using physiological indices is also supported by emotion theory, where more simplistic understandings of the basic emotions have evolved to include increasing nuance. For example, research often goes beyond

including between pure emotional states to examine emotions in terms of same-valence emotional blends and cross-valence mixed emotion (Watson and Stanton 2017), where multimodal emotion tagging is used to improve predictive modeling (Wang et al. 2015). In the present context, based on the dimensional theory of emotion, emotional states can be categorized into reciprocal dominant states (either positive or negative emotion prevailing), a co-inactive state (both positive and negative responses being inactive), and a co-active state (both positive and negative responses being active). Accordingly, these four emotional states can be quantified through the OO–CORR coupling.

The OO–CORR coupling may be predictive of attitudes via a number of theoretical pathways. First, facial expression can serve as a source of information directly influencing people's evaluation of ads. The "feelings-as-information" theory (Schwarz and Clore 1983; Schwarz et al. 2021) argues that individuals use their feelings as source information in judgment. A simple example of the theory's key proposition is that being in a positive mood, as opposed to a negative one, makes people more likely to form positive evaluations. Second, facial expressions provide feedback information in one's evaluation process. Hatfield, Cacioppo, and Rapson (1993) argued that one's facial expression, even a mimicry of another person, can provide feedback information to one's own emotional feelings, transferring a specific emotional state from the body to the mind. The idea of using facial expression as information in judgment also aligns with the Elaboration Likelihood Model's (ELM) arguments about emotion and persuasion. One particularly relevant pathway suggested by the ELM is that emotions serve as simple cues when cognitive elaboration is low (Petty and Briñol 2015). Under these conditions, emotions impact attitude in accord with the ad valence. For example, positive ads are evaluated more favorably than negative ones. Together, these theoretical frameworks suggest that facial expressions, whether as direct or feedback information, are automatically (mis)attributed to attitudes during evaluation.

It is worth noting that a key assumption underlying the use of OO–CORR coupling to predict attitudes here is that viewers engage in low cognitive elaboration during ad viewing (from the ELM perspective) or they are largely unaware of using their feelings as information (from the feelings-as-information perspective). Under these conditions, facial expressions can serve as simple cues or direct information for evaluation, which provides the foundation for us to explore the link between the OO–CORR coupling and consumers' attitude. Additionally, reality is often more complicated than what theories predict. While theories hypothesize the effect of positive and negative messages on human responses for the sake of abstraction and simplification, advertisements are rarely purely positive or negative; oftentimes they evoke a mix of emotions. This underscores the importance of studying the dynamic interplay of OO–CORR coupling and identifying features within this coupling that best predict consumer attitudes.

Coupling HR and SCL to Predict Recognition Memory

Like consumers' attitudes toward ads, memories of the ad and brand are also valuable outcomes of ad viewing. Whether examining attitudes or memories, as discussed earlier, both cases have revealed the physiological process–psychological outcome mismatch. The LC4MP argues that memory performance is a function of the resources allocated to encoding, storage, and retrieval sub-processes (Lang 2017). Encoding is foundational to recognition memory performance, depending on both resources allocated to and required by the message (Lang, Schwartz, and Mayell 2015). When resource allocation to the message exceeds the demand, it results in a sufficient information process leading to a good recognition memory; conversely, when resource allocation falls short, cognitive overload occurs and impairs recognition memory (Lang, Schwartz, and Mayell 2015).

According to the LC4MP, resource allocation varies based on two key message attributes (Lang 2017; Lang, Schwartz, and Mayell 2015). First, the number and magnitude of orienting responses elicited by the message's structural features impact the amount of resource allocation to encoding. Orienting responses are automatic attentional responses to novel and signal information occurring in one's surroundings (Graham 1979). In media viewing, orienting responses are triggered by structural features such as camera changes and voice changes, automatically directing resources to encoding and storing the message (Lang, Schwartz, and Mayell 2015; Potter, Lang, and Bolls 2008).

Second, resource allocation to encoding is also influenced by motivational systems activation. In the media viewing context, positive messages are expected to activate the appetitive system whereas negative messages activate the aversive system (Lang 2006). Early versions of LC4MP predict that increased

appetitive activation enhances resource allocation to encoding and storage (Lang et al. 2013, Lang, Schwartz, and Mayell 2015). The effect of aversive activation on encoding, however, depends on its intensity. Low to moderate aversive activation increases resource allocation to support threat identification, whereas extremely high aversive activation shifts resources toward decision-making processes (e.g., fight-or-flight responses), reducing allocation to encoding. In summary, the LC4MP predicts that more orienting responses and greater motivational system activation should lead to a higher level of resource allocation, thereby enhancing encoding memory, provided that motivational activation does not become extremely intense such that it causes cognitive withdrawal from the message.

Physiological measures are commonly used to assess the amount of resource allocation. HR is used as an indicator of resource allocation to encoding, reflecting both automatic and controlled processes. In the case of individual media viewing, HR deceleration indicates greater encoding (Lang, Potter, and Bolls 2009). Furthermore, motivational system activation is assessed by SCL, where a higher level of SCL suggests greater automatic resource allocation unless cognitive withdrawal occurs. Notably, higher SCL that reflects increased resource allocation occurs in response to positive messages as well as low to moderate levels of negative messages, as the result of the appetitive and aversive systems activation. As messages become excessively negative, individuals become more aroused and less attentive, resulting in poorer encoding. This pattern is characterized with an overall increased HR and SCL with poor recognition memory (Wang and Lang 2012). Overall the LC4MP and studies testing its propositions conceptually implied two distinct message processing states: a cognitive avoidance state as characterized with a high level of HR and SCL and an engagement state that reflects high attention and better encoding, as characterized with a low level of HR and a high SCL, particularly during the processing of moderately negative messages (Wang and Lang 2012). But again, these states were commonly discussed conceptually, based on separate statistical models using either HR or SCL as dependent variables, and were rarely tested collectively.

Given these two key factors jointly influence encoding memory per the LC4MP, we propose that coupling of HR and SCL, as an operationalization of the two factors as identified above, may offer a more effective way of identifying engagement levels, thereby improving our ability to explain and predict encoding memory. Specifically, coupling HR and SCL in a time-locked way for analysis may help us identify moments that viewers are truly in the high-engagement state and differentiate this state from other states. Thus, identifying their collective patterns and exploring how their characteristics of dynamics, such as how frequently each collective pattern occurs (*stability*), are associated with recognition memory may be a valuable approach to explain cases where these physiological indicators of resource allocation and recognition memory were disconnected.

The Current Study

The goal of this study is to re-analyze the data from Lee (2017) using a system-level dynamics perspective, exploring the extent to which the multimodal physiological responses can predict consumers' attitudes and recognition memory. By doing so, the present work provides theoretical and analytical insights into the mismatch observed by Lee et al. (2018) and Lee, Potter, and Han (2023) between media effect patterns found from physiological data and the corresponding psychological outcomes. Specifically, on the emotional dimension, the emotional content effects on facial expressions and self-reported attitudes were found to be distinct. On the cognitive dimension, while media aspects significantly affected HR activity, they did not show a significant relationship with visual or brand recognition memory in the previous research (Lee, Potter, and Han 2023).

We take a step toward arbitrating the physiological process–psychological outcome mismatch by examining OO–CORR and HR–SCL coupling in reference to valued advertisement outcomes. The OO–CORR coupling produces four distinct states for viewers at any given moment, drawn from the dimensional theory of emotion. The *positive emotional state* is characterized by high OO and low CORR, whereas the *negative emotional state* is characterized by low OO and high CORR. On the other hand, a *co-active emotional state* is characterized by high OO and high CORR, whereas a *co-inactive emotional state* is characterized by low OO and low CORR.

Similarly, the coupling of HR-SCL produces four distinctive states on top of the two states that early research implicated. First, a *high-engagement state*, as mentioned earlier, is characterized by low HR and high SCL. This is a state that is most likely to have a positive relationship with recognition memory, because low HR indicates a high level of resource allocated to process the information in general, and high

SCL increases the resources allocated to the encoding process in particular. Conversely, a *low-engagement state* is characterized by fast HR and low SCL, which is likely to have a negative relationship with recognition memory. The *uncoupled engagement state* is characterized by low HR and low SCL. Although this state involves a high level of attention, the low SCL indicates a lack of the second source of resource allocation, compared to the high-engagement state. Thus, participants in this state may or may not have sufficient resources available to encode the information, leading to a potential mismatch between HR activity and recognition memory. Finally, a *cognitive avoidance state*, as discussed previously, is characterized by high HR and high SCL. This is a state that likely involves identifying a threat followed by attention withdrawal from it, thereby inhibiting its processing. According to the defense cascade model (Bradley et al. 2001), such a state may be indicative of fight-or-flight responses triggered by perceived threats or cognitive overload.

It is anticipated that for either the emotional or engagement dimension, individuals will be in a dynamic transition between the above defined states during ad viewing. We expect that the stability of emotional and engagement states might impact one's attitudes and recognition memory, respectively. Broadly speaking, stability is an indicator of one's resilience to the evolving environment (Webber and Zbilut 2005). In this study, stability refers to the persistence of a particular emotional/engagement state over time, indicating the extent to which an individual maintains or returns to that state during ad viewing. A more stable state suggests a stronger tendency to remain in that state and greater resistance to shifting. Operationally, this means that an individual spends more time in that state or frequently revisits it. Based on the theoretical pathways of emotion's influence on attitude, we propose that:

H1a: The stability of the positive emotional state would positively impact individuals' self-reported attitudes toward the ad, brand, and purchase intention.

H1b: The stability of the negative emotional state would negatively impact individuals' self-reported attitudes toward the ad, brand, and purchase intention.

RQ1: How did co-active and co-inactive states associate with individuals' self-reported attitudes toward the ad, brand, and purchase intention?

For the engagement state, we hypothesize that greater stability in the high-engagement state—meaning more time in low HR and high SCL, which based on the LC4MP should allocate more resources to encoding—will enhance recognition memory about the ad and its advertised brand (H2a). On the other hand, greater stability of the low-engagement/cognitive avoidance state reflects reduced resources allocated to encoding and so will impair one's recognition memory (H2b and H2c). Thus,

H2a: The stability of the high-engagement state during ad viewing would positively predict individuals' recognition memory about the ad and the advertised brand.

H2b: The stability of the low-engagement state would negatively impact individuals' recognition memory about the ad and the advertised brand.

H2c: The stability of the cognitive avoidance state would negatively impact individuals' recognition memory about the ad and the advertised brand.

As discussed earlier, the uncoupled engagement state may or may not lead to sufficient resources available for encoding; thus, we ask:

RQ2: How did the stability of the uncoupled engagement state impact individuals' recognition memory about the ad and the advertised brand?

Method

Experimental Design

The study is a secondary analysis from Lee's experiment (Lee 2017) where a mixed design was used with a 2 (sports program–induced valence: positive, negative) × 2 (sports program–induced arousal: calm, arousing) × 2 (ad-induced valence: positive, negative) × 2 (ad stimuli instantiation) structure. The experiment was originally designed to test the effects of emotional content on individuals' physiological responses and viewing outcomes. All factors, except for the ad stimuli instantiation, were within-subject. The ad stimuli instantiation factor was the only between-subjects variable, allowing for the examination of two distinct sets of advertisements designed to evoke either positive or negative emotions. This design enhances the generalizability of the experimental stimuli by ensuring broader applicability across different ad variations (e.g., Jackson and Jacobs 1983; Slater, Peter, and Valkenberg 2015).

As shown in Supplementary Table S1, each ad was rotated within a 2 (sports program–induced valence: positive, negative) × 2 (sports program–induced arousal: calm, arousing) matrix, ensuring that each ad was paired at least once with each category of sports

program–induced emotions, thereby guaranteeing counterbalancing. The presentation order of these paired sports program–ad combinations was completely randomized.

Experimental Stimuli

National Collegiate Athletic Association (NCAA) men's basketball games from the university's team (the data collection site) were used to manipulate sports program–induced emotions, given the popularity of the basketball team within the university. The specific way of manipulating emotional valence and arousing levels for the basketball games is detailed in the supplementary file.

For ad stimuli, to control for ad and brand familiarity, 48 advertising stimuli in English were collected from outside of the United States (e.g., Australia, United Kingdom) to ensure that participants were unfamiliar with the brands and ads. This approach follows the guidelines set by Bellman, Wooley, and Varan (2016) and Norris and Colman (1994). Based on participants' self-reported emotional responses (i.e., how positive and arousing each ad was), ad and brand familiarity, and attitude to ad, a total of 16 ads varying in the length between 28 and 70 seconds, were selected as the final ad stimuli. Additional details regarding the stimuli can be found in a published work (Lee et al. 2018; Lee, Potter, and Han 2023).

Participants and Procedure

A total of 76 undergraduate participants (53 male, 21 female) from a large public university completed the experiment, with a $20 payment as their compensation.

Upon providing their consent, participants were seated on a comfortable couch in front of a 42-inch LCD monitor in the experimental lab. After physiological measures were set up (see the procedure in the supplementary material), participants completed a brief questionnaire containing demographic questions and the team identification scale to assess their connection to the university's men's basketball team.

Participants were informed that they would watch the final minutes of several games of the university basketball team but were not told about the memory test for the ad. After each of the eight sports broadcasts were viewed, a counterbalanced ad was presented immediately. Participants then completed a questionnaire assessing their attitudes toward the ad and the advertised brand as well as their purchase intentions for the advertised product/service. After the eight programming/advertising sequences, a recognition memory test regarding brands and scenes followed, and participants were debriefed at the end of the session. The entire procedure took approximately 90 minutes for each participant.

Measures

Physiological Measures

As mentioned in the introduction, the OO muscle group activation was used as an indicator of positive emotions, and the CORR muscle group activation served as a measure of negative emotions. SCL was measured through electrodermal activity (EDA) to assess autonomic arousal, and finally HR deceleration was used as a measure of resource allocation (Potter and Bolls 2012). Data preprocessing is detailed in the supplementary material, and all physiological data were averaged per second for analysis.

Brand and Visual Recognition

Encoding performance was evaluated through visual recognition tasks related to the advertised brands and other visual elements from the commercials (e.g., Lee, Potter, and Han 2023; Sparks and Lang 2015; Wang and Lang 2012). Participants were asked to respond "yes" or "no" to the following questions: "Did you see this brand logo while watching the commercial?" and "Did you see this exact scene during the commercial?" The brand recognition task included eight logos that participants actually saw during the experiment and another eight logos that were either altered versions of the original logos or the same logos paired with a different brand name, which served as foils. These logos were presented randomly on the screen. Additionally, eight images were taken from scenes in the advertisements, with eight foil images selected from different commercials with similar visual elements (e.g., identical actors or similar brand logos). To minimize order and fatigue effects, recognition probes were presented in a random order and displayed for 750 milliseconds, as controlled by DirectRT (Jarvis 2012). Participants were instructed to respond as quickly as possible, pressing the appropriate button. A practice session was provided before the main task. Correct responses were scored as 1 and incorrect responses as 0. We further converted the participants' responses into hit rate (correctly recognizing targets), false alarm (mistakenly recognizing foils), and memory sensitivity (the difference between z-scored hit rate and false alarm).

Attitude Toward Advertisement

Attitude toward the ad (Aad) was evaluated using a six-item semantic differential scale, modified from previous studies (e.g., Miniard, Bhatla, and Rose 1990; Wang and Lang 2012), measuring dimensions such as unpersuasive/persuasive, uninformative/informative, unbelievable/believable, not likable/likable, unattractive/attractive, and unappealing/appealing.

Attitude Toward Brand

To assess attitude toward the advertised brand (Ab), four 7-point semantic differential scales were adapted from Krosnick et al. (1993). This scale included items such as bad/good, unpleasant/pleasant, and unfavorable/favorable.

Purchase Intention

To measure purchase intention, Yi's (1990) seven-point semantic differential scale was utilized, which includes three items: unlikely/likely, improbable/probable, and possible/impossible. This scale has been widely utilized in previous research (e.g., Kwak, Jaju, and Puzakova 2011). The specific question asked was, "If this product/service were available for purchase, how likely are you to buy it the next time you need to make a purchase?"

Data Analysis

As this current study focuses on how the engagement and emotional state stability impact recognition memory and viewing outcome measures, the emotional variables of sport programs and advertisements were used as covariates in the statistical models.

The ad duration varied in this experiment, with the mode being 30 seconds (10 out of 16). In the current analysis, we focused on physiological responses recorded during the first 30 seconds of viewing of all ads, except for one ad that lasted 28 seconds. For that case, only the actual ad viewing time (28 seconds) was analyzed. The choice of analyzing the first 30-second data aligned with previously published work using this dataset (Lee 2017; Lee, Potter, and Han 2023), such that the results are more comparable across studies. Psychophysiology data in the desired time windows were further cleaned using the *tsclean()* function from the *forecast* package in *R* (Hyndman and Khandakar 2008). The *tsclean()* function first regressed out any seasonal trends in the time series and then identified outliers defined as values below the 25th percentile minus three times interquartile range (IQR) or above the 75th percentile plus three times IQR. The identified outliers were replaced by linearly interpolated values of the anchor points around the outliers (i.e., connecting a line between the anchor points). To account for baseline change of physiology signals throughout the experimental session, we converted the cleaned data into change scores by subtracting the value 1 second before each ad onset from every subsequent second during ad viewing. In accordance with the conceptualized multimodal physiological states, we discretized the physiology change scores. To attempt this, we computed the median value of each physiological signal (after converting it to change score) within each participant. We then did a median split to obtain binary-coded (high versus low) data for each physiology measure.

Multidimensional Recurrence Quantification Analysis (MdRQA)

The binary-coded physiology signals in this study were further used to construct multimodal states, as we conceptualized earlier (see Figure 2 for illustration). Recurrence quantification refers to a family of nonlinear dynamical analyses that identify recurring patterns of system-level activity (Marwan et al. 2007). This approach classically focuses on a single signal and utilizes Takens' time-delay embedding to recreate the dynamics of the system from which the signal was recorded (Takens 1981). However, MdRQA was recently introduced by Wallot, Roepstorff, and Mønster (2016) to enable the analysis of multivariate data (e.g., collective HR and SCL patterns). The recurrence plot is the primary outcome of MdRQA, which is a matrix containing pairwise comparisons between every time point in a signal. Points that are highly similar to each other are flagged as recurrent in the matrix, which indicates that the system has returned to a previous pattern during those times. The recurrence plot is then quantified to extract dynamical descriptions of a system such as system-level stability, determinism, and Shannon entropy. In particular, recurrence rate (RR) represents the percentage of recurrent points within the recurrence plot and was used as the stability indicator in this current study. MdRQA is a powerful framework for analyzing physiological data because it makes minimal assumptions about the underlying data distribution, can detect nonlinear relationships, and is robust in handling noise and missing observations (Webber and Marwan 2015).

Previous research has used MdRQA to identify relationships between physiological activity and psychological processes. For example, Amon et al. (2022)

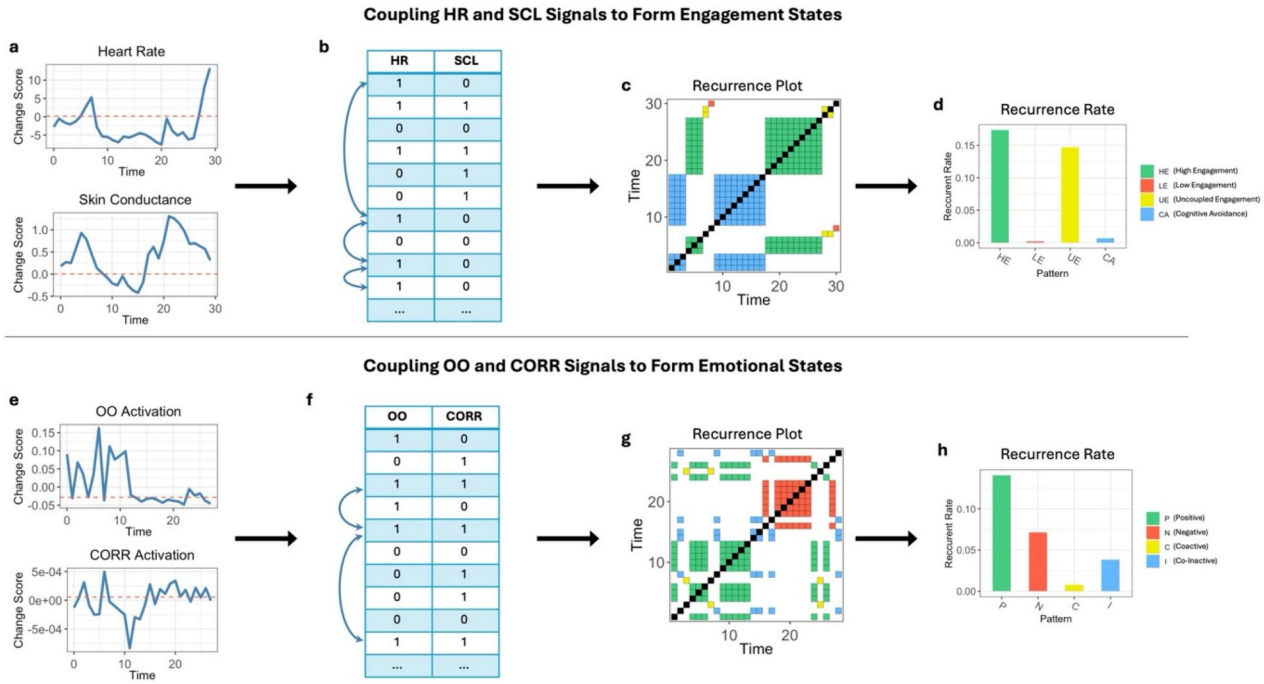

Figure 2. Procedure of building multimodal physiological states.

Notes. The procedure of building multimodal physiological states started from the preprocessed physiological change scores, using one second before ads onset as baseline (a, e). The change scores were discretized to binary-coded variables using median split. The median values (red dashed lines) were computed within each subject and across stimuli (b, f). We then used multidimensional recurrence quantification analysis (MdRQA) to build engagement states from the coupling of heart rate (HR) and skin conductance level (SCL) signals, and emotional states from the coupling of orbicularis oculi (OO) and corrugator supercilii (CORR) signals, on a second-by-second basis. MdRQA looks for recurrences of each multimodal state. Example recurrence instances are depicted in b and f. We then created recurrence plots depicting when these multimodal states appeared during ads viewing (c, g). Each state's recurrence rate corresponds to the proportion of the area it occupies in the plot.

predicted workplace stress and personality traits from collective patterns of HR, step count, and sleep duration. MdRQA has also been applied to measure interpersonal physiological synchrony in three-person collaborative team settings and predict task related frustration levels and team outcomes (Algumaei et al. 2023; Håkonsson et al. 2016; Mønster et al. 2016; Wallot, Roepstorff, and Mønster 2016). The current study applies MdRQA to examine collective patterns occurring across HR and SCL and the CORR and OO muscle groups, analyzed within individuals. Specifically, we implemented the modified MdRQA procedure developed by Amon, Vrzakova, and D'Mello (2019) that binarizes the data prior to analysis and calculates the frequency of each collective activity pattern separately (e.g., Necaise et al. 2021). This approach allows us to focus on the frequency of specific physiological states, such as states of high-engagement when SCL is elevated and HR is depressed. Our main strategy was to use the RR of multimodal engagement states (coupling between HR and EDA) to predict recognition memory for ad content and use the RR of emotion states (coupling between OO and CORR) to predict self-reported attitudes.

Further analyses were conducted with multilevel modeling. In the models, either recognition memory scores or self-reported attitudes were the dependent variable. The independent variables included the RR of the four engagement states or the four emotion states, as we conceptualized earlier. The model also included the three experimental factors (sports program valence, arousal, and ad valence) and their interactions as covariates, as designed in the Lee (2017) study. Assessments of multicollinearity showed that the variance inflation factor was reasonable between our independent variables (less than 2), indicating that multicollinearity was not an issue. Random intercepts were added at the subject level. No random slopes were included due to model convergence issues.

Results

The main objective of this study was to assess the feasibility of using the RR of multimodal

psychophysiology states to predict advertisement effectiveness. We specifically focused on two types of multimodal states: the emotional states, indicated by the coupling of time-locked OO and CORR signals, and the engagement states, indicated by the interplay between HR and SCL signals. The goal was using the emotional states to predict attitudes and the engagement states to predict recognition memory about ad content.

Predicting Self-Reported Attitudes from Emotional States

Our first set of hypotheses (H1a, 1b) and RQ1 focused on the relations between RR of emotional states and self-reported attitudes, including purchase intention, attitudes to brand, and attitudes to ads. Neither H1a or H1b were supported, as our data revealed no significant relations between any of the attitudinal measures and RR of the positive or negative states. As for RQ1, we found that increased RR of the co-active state significantly predicted less favorable attitudes to the ads and brand and also lower purchase intention. RR of the co-inactive state did not predict any of the attitudinal measures. Table 1 summarizes the findings related to emotional states.

Predicting Recognition Memory from Engagement States

We hypothesized that a greater RR of the high-engagement state (low HR and high SCL) would predict better recognition memory of ads content (H2a), whereas greater RRs of the low-engagement and cognitive avoidance states would have detrimental effects on memory performance (H2b and c). Each type of recognition—visual scene recognition and brand recognition—was tested by hit rate, false alarm rate, and the overall memory sensitivity. Better recognition memory was expected to be associated with greater hit rate and overall memory sensitivity but lower false alarm rate.

Brand recognition. In line with H2a, data revealed that a greater RR of the high-engagement state predicted increased hit rate of the advertised brand (i.e., accurately recognizing brands that actually appeared in the ads), without inflating false alarm (i.e., mistakenly recognize foil brands that did not appear in the ads), and hence overall enhanced memory sensitivity; see Table 1. Also, as expected, a greater RR of the low-engagement state predicted increased false alarm rate but did not predict hit rate or sensitivity. Memory performance around the advertised brand was not associated with RRs of the other two engagement states.

Visual scene recognition. As for the recognition memory about visual scenes depicted in the ads, unexpectedly, RR of the high-engagement state was not a significant predictor for hit rate, false alarm rate, or sensitivity. RR of the cognitive avoidance state, as expected, had a positive relation with false alarm rate when recognizing visual scenes. Moreover, RR of the uncoupled engagement state was found to have positive impacts on hit rate and sensitivity of visual scene memory.

In summary, H2a was partially supported because a greater RR of the high-engagement state benefited brand but not visual scene recognition memory. H2b was also partially supported because a higher RR of the low-engagement state predicted increased false alarm rate of brand recognition, but not for visual scene memory. H2c was partially supported in that, as expected, higher RR of the cognitive avoidance state was associated with inflated false alarm rate of the visual scene recognition memory, but not for brand memory. For RQ2, a greater RR of the uncoupled engagement state was associated with increased hit rate and memory sensitivity of visual scene but not brand. Table 2 summarizes the findings related to engagement states.

Post Hoc Analysis: State Stability across Viewing Conditions

Data above demonstrated that the RRs of multimodal physiological states could predict ad effectiveness. The

Table 1. Effects of emotional states recurrence rate on self-reported ad attitudes.

	Positive (High OO, Low CORR)			Negative (Low OO, High CORR)			Co-active (High OO, High CORR)			Co-Inactive (Low OO, Low CORR)		
	Beta	*SE*	*p*	*Beta*	*SE*	*p*	*Beta*	*SE*	*p*	*Beta*	*SE*	*p*
Brand attitude	0.201	0.370	.587	0.171	0.400	.669	**−0.887**	**0.404**	**0.028***	0.112	0.434	.796
Ad attitude	0.483	0.378	.202	0.490	0.409	.231	**−1.001**	**0.412**	**0.015***	0.529	0.443	.233
Purchase intention	0.352	0.407	.386	0.333	0.439	.449	**−1.220**	**0.444**	**0.006****	0.115	0.478	.809

Notes. "Low" and "High" are relative to each other as they were created based on change scores from baselines. Bolded values indicate significant results with a threshold of $p < .05$.
*** $p < .001$, ** $p < .01$, * $p < .05$.
OO = orbicularis oculi; CORR = corrugator supercilii.

Table 2. Effects of engagement states recurrence rate of recognition memory.

	High Engagement (Low HR, High SCL)			Low Engagement (High HR, Low SCL)			Uncoupled Engagement (Low HR, Low SCL)			Cognitive Avoidance High HR, High SCL		
	Beta	*SE*	*p*	*Beta*	*SE*	*p*	*Beta*	*SE*	*p*	*Beta*	*SE*	*p*
Brand recognition												
Hit rate	**0.318**	**0.133**	**0.017***	0.215	0.142	0.131	0.156	0.139	0.263	0.120	0.126	0.341
False alarm	0.067	0.146	0.644	**0.311**	**0.156**	**0.046***	0.284	0.152	0.062	0.234	0.138	0.091
Sensitivity	**0.705**	**0.306**	**0.022***	0.415	0.327	0.204	0.235	0.319	0.462	0.140	0.290	0.630
Visual recognition												
Hit rate	0.150	0.117	0.198	0.094	0.125	0.451	**0.314**	**0.122**	**0.010***	0.039	0.111	0.724
False alarm	0.240	0.140	0.087	0.136	0.150	0.366	0.232	0.146	0.113	**0.343**	**0.133**	**0.010***
Sensitivity	0.531	0.310	0.088	0.343	0.331	0.301	**0.721**	**0.323**	**0.026***	0.013	0.294	0.965
Overall recognition												
Hit rate	**0.248**	**0.091**	**0.007****	0.164	0.098	0.094	**0.234**	**0.095**	**0.015***	0.078	0.087	0.368
False alarm	0.151	0.100	0.131	**0.219**	**0.107**	**0.041***	**0.237**	**0.104**	**0.024***	**0.268**	**0.095**	**0.005****
Sensitivity	0.372	0.380	0.329	−0.070	0.407	0.863	0.039	0.397	0.922	−0.551	0.361	0.127

Notes. "Low" and "High" are relative to each other as they were created based on change scores from baselines. Bolded values indicate significant results with a threshold of $p < .05$.
$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$. "*Overall Recognition*" refers to the findings that combined memory scores from both brand and visual scene recognition.
HR = heart rate; SCL = skin conductance level.

results indicated that if an ad's goal is to increase viewers' liking of the ad, brand, and purchase intention, an ad that can suppress the co-active state is favored. On the other hand, if the goal is to enhance one's recognition memory about the advertised brand, an ad that can elicit a high-engagement state is favored. Last, if the goal is to enhance one's recognition memory about the visual information of the ad, an ad that can elicit an uncoupled engagement state is favored. These results prompted a post-hoc analysis to assess which types of ads facilitate or inhibit the recurrence of the abovementioned three states. The post hoc analysis serves two key purposes. First, it tests whether the relations between message features and multimodal state stability align with theoretical predictions from previous literature. Second, it provides practical insights into message selection and design when an ad campaign has a particular goal.

In the post hoc analysis, we first ran three repeated-measure analysis of variance models, using the RR of co-active emotional state, high-engagement state, or uncoupled engagement state as the dependent variable. The independent variables were ad valence (positive or negative) crossed by sports program valence (win or loss) crossed by sports program arousal (lopsided or close). Results revealed a significant main effect of ad valence on RR of co-active state (F (1, 584) = 24.08, $p < .001$), indicating that the co-active emotional state was more likely to occur when participants watched negative-valence ads.

For the high-engagement state, we found a main effect of ad valence (F (1, 584) = 8.12, $p = .004$) and a main effect of sports program valence (F (1, 584) = 7.39, $p = .007$), such that the RR of high-engagement state was higher in negative- than positive-valence ad and higher in ads following a positive (win) than negative (loss) sports program.

Last, for the uncoupled engagement state, we found 2 two-way interaction effects: an ad valence by sports program arousal interaction (F (1, 584) = 6.24, $p = .013$) and a sports program valence by arousal interaction (F (1, 584) = 3.97, $p = .047$); see Figure 3. No other significant main or interaction effects were observed with the three multimodal states assessed here.

Figure 4 presented the three meaningful states in the order of their RRs across the eight viewing conditions in our study. As shown in Figure 4, the co-active emotional state was the most likely to recur in negative-valence ads followed by an arousing, negative-valence sports program. On the other hand, positive ads followed by an arousing, positive-valence sports program seemed to suppress the co-active state. As for the high-engagement state, it was the most likely to recur in negative-valence ads followed by a calm, positive-valence sports program. Meanwhile, the high-engagement state seemed to be suppressed during positive-valence ads, followed by an arousing, negative-valence sports program. Last, the uncoupled engagement state was most likely to recur in positive ads followed by an arousing, negative-valence sports program and the least likely to recur in negative-valence ads followed by an arousing, positive-valence sports program.

Discussion

Leveraging recent advancements in system-level dynamics (Han et al. under review), this study took a multimodal approach to addressing the traditionally

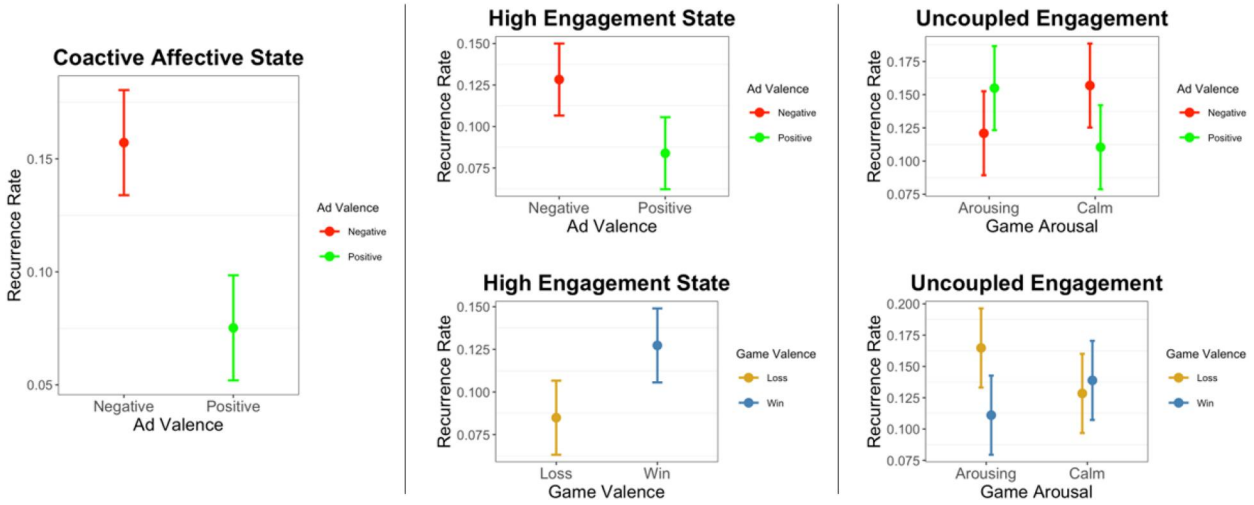

Figure 3. Recurrence rates of multimodal states by stimuli factors.
Note. Error bars indicate 95% confidence intervals. Another set of pairwise comparisons was conducted to examine differences in recurrence rates across the four engagement/affective states within each viewing condition. The corresponding results are reported in the supplementary file.

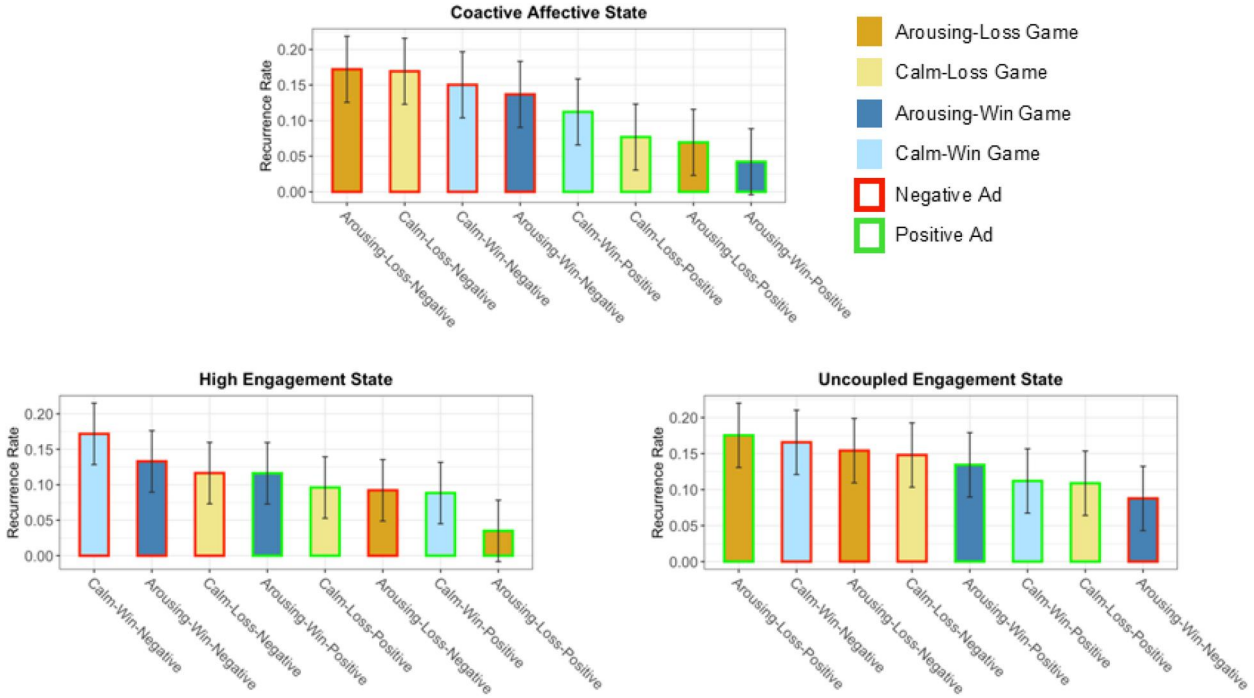

Figure 4. Recurrence rates of multimodal states by message types.
Note. The bars show the estimated mean recurrence rate (RR) across subjects for each message type. Error bars indicate 95% confidence intervals.

observed mismatch between physiological responses and psychological outcomes. Four emotional and four engagement states were identified from the time-locked OO–CORR coupling and HR–SCL coupling, respectively. The findings show that, during advertisement viewing, the co-active high OO–CORR emotional state negatively predicted self-reported attitudes toward the viewed ads, brand, and purchase intention. Meanwhile, the high-engagement state, defined by the coordination of low HR and high SCL, was associated with increased recognition memory toward advertised brands. In addition, the uncoupled engagement state indicated by low HR and SCL increased recognition memory of advertisement visual scenes. To our knowledge, this is the first study demonstrating the feasibility of predicting advertisement effectiveness from

multimodal physiological states. Notably, previous analyses with this dataset did not observe significant relationships between isolated physiological signals and ad effectiveness (Lee et al. 2018, Lee, Potter, and Han 2023). In contrast, the current study shows evidence that nuanced, higher-order viewer states can be captured dynamically and multimodally to predict valued ad-viewing outcomes. As opposed to examining averages of individual signals, we forward a new multimodal analytic approach to enhanced predictive power of media message effectiveness, with potential to draw coherence to LC4MP-related research.

OO–CORR Coupling for Attitudinal Outcomes

While Lee et al. (2018) found that only attitudes toward the ad were impacted by two independent effects (program and ad-induced valence), no other attitudinal measures (i.e., toward the brand and purchase intention) were found to be predictable. This study, by directly analyzing real-time coupled physiological processes, demonstrates that the co-active state predicts consumer attitudes across all three measures. Specifically, a decrease in the co-active state corresponds to more favorable attitudes toward ads, brands, and purchase intentions. The co-active state was lowest with positive ads following arousing positive programs as compared to other viewing conditions (Figure 4), indicating the most favorable attitudes. Conversely, the co-active state was highest with negative ads following negative programs, regardless of their arousal level, indicating the least favorable attitudes. Compared to Lee et al. (2018), the conclusions here regarding which message combination leads to the best and worst attitudes more closely align with the LC4MP (Eckler and Bolls 2011; Wang and Lang 2012), the ELM, and the feelings-as-information theory. The multimodal approach (i.e., OO–CORR coupling) provides improved granularity when investigating the theories.

After identifying the effects of the co-active state, the question of why the co-active state predicted consumer attitudes remained. One possibility is that the relationship between the co-active state and attitudes suggests mechanisms not explained in the ELM and feelings-as-information theories. Attitude formation might not be a simple summation of positive and negative feelings. The negative relationship between the co-active state and attitudes in our data implies two additional mechanisms of attitude formation in advertising. First, attitude formation might involve concurrent activation of the two motivational systems at any moment. When both systems are activated, ad viewers experience psychological discomfort because of the conflicting emotions they feel from the ads. This psychological discomfort may lead to emotional and cognitive uncertainty when they evaluate their attitude toward the ad and brand and purchase intention, which directly reduces their favorability over the ads.

A second explanation for the unexpected finding may lie in memory, where memory of the advertised objects influences attitude formation (Fazio 2007). As predicted by the LC4MP, previous studies consistently showed better recognition and stored memory for co-active messages where both negative and positive content are present, compared to messages with only negative or positive content (e.g., Lang et al. 2013). This is because co-active content elicits the activation of both motivational systems—thus a co-active state—while purely negative or positive content triggers only one motivational system. Notably, this effect occurs only when the co-active message does not contain highly arousing negative content, because highly arousing negative content would elicit extremely high activation of the aversive system, inhibiting information intake and thus impairing memory.

While co-active messages are typically better remembered, the negative aspect of it might be even better remembered compared to the positive aspect of co-active content due to the negativity bias (Lang et al. 2013). Hence, together with Fazio's conceptualization that attitude formation is a function of memory, we suspect that the better memorized negative content in co-active messages may influence one's attitude to a greater extent than the positive content. Therefore, stronger stability in co-active emotional states may suggest a better memory of ad content, and the enduring accessibility of negative content within the memorized content may drive a less favorable evaluation of the ad. Our data did provide some empirical support for this relationship between the co-active emotional state, memory, and attitude. Specifically, we found that the co-active emotional state not only impacted one's attitudes as reported earlier but also had a significant positive association with brand recognition memory sensitivity ($b = .57$, $SE = .28$, $p = .04$; though not with visual recognition memory, $b = -0.23$, $SE = .29$, $p = .43$), which supports the LC4MP argument that the co-active state enhances memory. Taken together, this study suggests a possibility of integrating the LC4MP and Fazio's research on attitude for a better understanding of information processing and attitude formation. Future

research should empirically test the above proposition that a co-active emotional state will lead to better memory for negative content than for positive content, presumably within a co-active message viewing context, and examine the extent to which this differential memory serves as a mechanism shaping attitudes toward the message and the brand.

HR–SCL Coupling for Recognition Memory

This study also found that brand recognition memory was enhanced by the high-engagement state (low HR, high SCL), whereas visual scene recognition was improved by the uncoupled engagement state stability (low HR, low SCL). This suggests a promising evaluation tool when one needs to differentiate the goal of enhancing brand and visual recognition memory. More importantly, it implies that the mechanisms underlying brand and visual scene recognition may be distinct from each other. Because the high and uncoupled engagement states are similar in HR levels but different in SCLs, the arousal level (as indicated by SCL) might be the key factor that determines the type of recognition (brand or visual) being benefited.

The arousal-based competition (ABC) theory (Mather and Sutherland 2011) provides valuable insights into our findings here. The ABC theory argues that when one experiences a high arousal level, the encoding and consolidation of information is enhanced for those with high priority for processing. Priority is determined by the bottom-up perceptual salience and the top-down relevance. For this study, brands in advertisements are believed to have high priority. The brands are typically presented very prominently against their background, making them stand out (i.e., with high bottom-up perceptual salience). Thus, when viewers are in the high-engagement state, their high-arousal state, based on the ABC theory, facilitates the processing of stand-out features in video content, which in this case, is the brand. Additionally, when the viewers are motivated to identify the brand during ad viewing, the brand then has top-down relevance, which also elevates its priority in the attention resource competition. In other words, brand exposure in advertising viewing is driven by both bottom-up salience and top-down relevance, resulting in strong encoding of brand information under high-arousal states, especially when accompanied by high attentional engagement (indicated by low HR).

In contrast, objects in the visual scene recognition test tend to be less salient. Compared to the stand-out feature of brands, objects in those scenes often present visual information more uniformly without distinct priority cues (see Supplementary Figure S2 as an example). According to the ABC theory, when elements in the scenes are equally prominent, a high-arousal state leads to attention competition among them, thereby impairing overall scene memory. A low-arousal state in this case benefits scene memory. This is exactly what we found in this study such that the uncoupled engagement state which is a high-attentive but low-arousal state significantly enhanced scene recognition memory.

Furthermore, the different impact of engagement state on the three memory measures (hit rate, false alarm, and sensitivity) suggests that each engagement state may influence the encoding process in different ways, without a consistent mapping between HR and memory or between SCL and memory (see Table 2). Rather, it may be the coupling of HR and SCL that together contributes to overall memory performance.

Finally, similar to the CORR–OO coupling, this study, compared to Lee and colleagues' studies using the same dataset, provides empirical evidence that suggests greater coherence to the LC4MP. Without testing the mediating state of human responses during ad viewing, Lee, Potter, and Han (2023) found very limited effects of the program-induced valence, arousal, and ad-induced valence on memory outcome. Specifically, they found only two pairwise comparisons at the significance level, both of which are for visual recognition memory: (1) Visual recognition memory was better for positive ads compared to negative ads when following arousing positive programs, and (2) visual recognition memory was better for negative ads following calm positive programs than for those following arousing positive programs. Given that the uncoupled engagement state stability was positively associated with visual recognition memory, as found in this current study, we further analyzed the role of the uncoupled engagement state in the above two comparisons. It turns out that the uncoupled engagement state indeed increased for positive ads for the first comparison (in line with results from Lee and colleagues) and for the negative ads following calm positive programs in the second comparison (again, in line with Lee and colleagues' findings; see Figure 4). The two-way interactions we found and reported in the post hoc analysis section, as compared to the three-way interaction found in Lee, Potter, and Han (2023), suggests a greater statistical power for testing the memory and engagement state relationship. Therefore, this engagement state approach might not

only show consistency with previous findings but also provide more coherent and robust evidence when using the uncoupled engagement state stability as one indicator for visual recognition memory.

Similarly, the stability of the high-engagement state provides a stronger indicator for brand recognition memory compared to the previous media effect approach. In Lee, Potter, and Han (2023), no message effect was found for the brand recognition memory. On the other hand, they did find lower HR, suggesting greater resource allocation, for negative ads compared to positive ads following calm positive programs, which based on the LC4MP should result in better recognition memory. But the brand recognition data did not differ between these two viewing conditions.

While Lee, Potter, and Han (2023) did not support the LC4MP argument, testing the mediating state on recognition memory using the high-engagement state stability, as demonstrated in this study, did support the LC4MP prediction. With the stability of the high-engagement state where HR and SCL levels were temporally coupled and considered collectively, this study did find that the negative ads produced greater high-engagement state stability, which leads to better brand recognition than positive ads, with negative ads following calm positive programs producing the best brand recognition. Hence, this finding is consistent with what Lee et al. (2023) found with HR. Therefore, this multimodal approach together with directly testing through the mediating state rather than through the message features provides a more aligned assessment with theoretical arguments. In turn, it again suggests that the underlying pathway from message features to the body responses as the mediating state to the viewing outcomes such as memory scores is not simply a stimulus–response media effect; rather, the whole sequence of the effect from stimulus to body response to outcomes should be carefully examined (with no causal relationship between body response and outcomes indicated here).

A Framework for a Systematic Testing of Media Exposure–Physiological Process–Psychological Outcome

The multimodal physiological approach introduced and tested in this study indicates the possibility of addressing the long-standing unresolved mismatch between physiological processes and psychological outcomes. By directly evaluating bodily responses and their relationship to psychological outcomes, this approach is particularly valuable for studying complex message contexts. For example, consider the message sequence effect on memory which is a matter of the appetitive and aversive motivational systems' activation decay, reactivation, and their dynamic interaction. Due to these complexities, previous studies have necessarily narrowed their scope of inquiry and, in the process, consistently addressed the challenge by using highly controlled media content, for example, varying the emotional valence of the preceding program while controlling the emotional content of the subsequent advertisement (Lee, Potter, and Pedersen 2019; Wang and Lang 2012). Even in Lee's (2017) more complicated design, the variation in emotional content was limited to three factors: the emotional valence and arousal of sports programs and the valence of advertisements. Few studies have simultaneously tested the emotional valence and arousal of both preceding programs and advertisements, likely due to the complexity of the physiological responses involved. Alternatively, this study offers a novel approach to measuring dynamic interactions among multiple physiological responses, taking a step toward untangling the effects of complex exposure scenarios with many narrative and emotional shifts.

Studying state stability, or how a system falls into, maintains, and returns to a specific state, is a fundamental first step toward a nonlinear dynamic understanding of system-level behavior (Thelen and Smith 1994). Uncovering system states and stabilities paves the way for more in-depth understandings of dynamics, including state transitions (also called phase shifts) and other dynamic features involved in ad viewing. Future studies can leverage recurrence plots generated in this study to analyze moment-to-moment state transitions, offering a more fine-grained view of how ads and preceding programs jointly shape the temporal structure of physiological states.

Limitations and Future Research

Whereas the impact of emotional states on consumer attitudes is consistent across all the attitudinal measures, the effect of engagement states on recognition memory depends on the type of recognition memory (Table 1). Future research is needed to untangle these more nuanced effects through literal or conceptual replications that test the generalizability of engagement and emotional states as predictors of message effectiveness across various contexts. Furthermore, messages used preceding advertisements are basketball games. Although we successfully manipulated their

emotional valence and arousal levels, additional work is needed to determine how these effects generalize to other viewing environments, such as entertainment programs and television shows.

Additionally, our analyses were based on physiological responses during the first 30 seconds of ad viewing to match the previous works conducted by Lee et al. (2018); Lee, Potter, and Pedersen (2019); and Lee, Potter, and Han (2023), allowing for more precise comparison between our results and theirs. In supplementary material, we present results analyzed with full ad lengths (Tables S2 and S3). This supplementary work confirmed the statistically significant negative associations between the stability of co-active emotional state and self-reported attitude measures, demonstrating its robustness. Although this supplementary analysis showed similarly positive associations between the engagement state and recognition memory, the relationship fell just outside of statistical significance for the relationship between high-engagement state and brand recognition memory ($p = .078$; $p = .174$ for the uncoupled engagement state and visual scene memory). Given that some researchers and statisticians argue for examining statistical significance along a continuum (McShane et al. 2019), we take these findings in partial support of those identified with the 30-second data. Importantly, this difference may be due to the dynamic and nonlinear nature of physiological activities. In particular, SCL is typically non-stationary (i.e., changing mean and standard deviation across the time series), since SCL tends to decline over time after an initial increase. For this reason, the HR–SCL coupling may not be directly comparable for data with varying lengths, which is the case with the stimuli used in this study.

Another analytic decision we made was to create the emotional and engagement states by median-splitting physiological signals within each participant. This decision closely follows a methodology developed by Amon, Vrzakova, and D'Mello (2019) and Necaise et al. (2021), which allow us to interrogate the dynamics of discretized cognitive and affective states during ad viewing. This median split method can be particularly effective for OO and CORR signals because activations of these facial muscle groups typically exhibit large bursts from a low inactive level. HR and SCL, on the other hand, do not have this "bursty" profile. Consequently, instances of misclassifications could occur, which may partially explain why the results for HR-SCL coupling are more analytically sensitive than the OO–CORR coupling data. Despite this limitation, the median split method aligns well with theoretical conceptualizations of engagement and emotional states and thus are valuable for testing theories like LC4MP. Moreover, although MdRQA has been previously applied to analyze continuous time series (Wallot, Roepstorff, and Mønster 2016), the combination of MdRQA and state stability analyses on continuous time series, to our best knowledge, has not been developed yet. Given the novel nature of the approach, we opted to prioritize interpretable physiological states. That is, typical recurrence quantification analysis only looks at time points as either recurrent or non-recurrent, without revealing information about the time points underlying values. We overcame this limitation by adopting a pattern analysis extension that projects information about the values underlying the recurrent points onto the recurrence matrix. This process goes beyond identifying how repetitive a system's states are to what states are visited, how often, and their relationship to meaningful outcomes, overall providing higher resolution when understanding system dynamics. Nonetheless, future replication studies are needed to assess the robustness of these findings using different sets of physiological data.

Conclusions

This study provides a step toward the theoretical integration of the LC4MP, the ELM, and feelings-as-information for evaluating advertising effectiveness. While the LC4MP explains and predicts the impact of message features on physiological processes and memory, consumer attitudes are not its focus. Recognizing that consumer attitudes are critical variables for advertising practitioners and scholars, this study expands the LC4MP by adding the relationship between physiological processes and consumer attitudes, offering a valuable framework for advertising and marketing research.

The findings have practical implications for brand promotion, indicating that positive ads following positive arousing programs produce the most favorable attitudes and support brand memory. On the other hand, negative ads following positive calm programs produce the best brand memory, but at the cost of low brand attitudes. However, if the goal is to enhance visual scene memory presented in ads (e.g., public service announcements), then positive ads following arousing negative programs are most effective, also fostering good attitudes toward the ad.

By adopting a system-level dynamics perspective, this study addresses the triangular relationship among message features, physiological processes, and memory

and attitudinal outcomes. In doing so, we proposed a relatively novel approach to understanding more complex media scenarios and established new multimodal measures for advertisement effectiveness that reflect nuanced yet interpretable viewer states. The findings provide greater coherence to the literature by bridging the physiological process–psychological outcome mismatch and mapping better with theoretical arguments.

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