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Can Emotions Be Used as Keywords for Text-Based, Search-Engine Advertising?

Pengyuan Wang[a], Anindita Chakravarty[a], and Jian Yang[b]

[a]Terry College of Business, University of Georgia, Athens, Georgia, USA; [b]Verizon Media, Sunnyvale, California, USA

ABSTRACT
Click-through rates (CTR) of search-engine advertising remain elusive, thus triggering the need for more research on ad effectiveness. Using simple regression techniques on a data set of 110,000 search query–text ad pairs, we show that it may be meaningful for advertisers to target search queries by (1) using the emotion of the user as indicated by an emotion word in the search query and, then, (2) using positive emotion content in their ads to achieve congruency with the search-query emotion. The results indicate non-spurious correlations that advertisers might consider in their search engine advertising strategies.

KEYWORDS
Emotional appeals; advertising

Introduction

Digital advertising spending worldwide amounted to 325 billion USD in 2019. Out of this, search engine advertising represents a vital component.[1] Also called sponsored ads, they are especially popular because they gain 1.5 times as many conversions from click-throughs as organic search results.[2] It is therefore not surprising that worldwide spending on sponsored ads reached 106.5 billion USD in 2019. Given the financial importance of sponsored ads,[3] advertisers are troubled by low click-throughs of these ads. For instance, research on 623 million unique search queries and corresponding sponsored ads on multiple search platforms reveals that almost 90% of ads have no clicks (Zhang et al. 2014). Low click-through rates (CTR) are of concern because click-throughs are vital metrics of brand awareness and brand visibility (Chan, Wu, and Xie 2011; Drèze and Hussherr 2003). In this sense, CTR represents a relevant metric of sponsored ad effectiveness and more research is needed to understand factors that might improve CTRs.

Sponsored advertising in search engines (in this study, we specifically refer to text ads displayed upon search queries) presents a relatively unique setting to study questions regarding improving CTRs. In this setting, we observe a signal from a user (i.e., a search query) that can tell us about a user's state and what the user is seeking. This provides a unique opportunity to understand the interplay between user motivations as expressed in the search query and the likelihood that the user will click on a sponsored ad (we refer to as *ad* hereafter) displayed by the search engine. Yet, we find that there is little research about how digital advertisers should target specific search queries based on keywords in the query. Though the relevance of an ad to the expressed product need in the query is critical, we note that search-engine queries could be phrases or sentences with words over and beyond the simple product or service of interest. These extra words might provide information about user mindsets that could be useful to digital advertisers. In particular, in this research, we are interested in the use of any word that depicts some form of emotion in a search query (we refer to this as *emotion word* hereafter). If the use of an emotion word implies that the user is feeling/anticipating some emotion in the search process, will an ad displayed upon a search query embedded with an emotion word likely generate significantly different CTRs than if it is displayed upon a search query without an emotion word? For example, as we show in Figure 1, we conducted two Google searches. In one search, our query was "vacation trip," and in the other search, our query was "vacation trip relaxing." Given that "relaxing" is an expression of an emotion, can we expect the sponsored ad in the query with the emotion word

CONTACT Anindita Chakravarty achakra@uga.edu Terry College of Business, University of Georgia, C327 Benson Hall, Athens, GA 30602, USA.
Pengyuan Wang (PhD, University of Pennsylvania) is an assistant professor of marketing, Terry College of Business, University of Georgia.
Anindita Chakravarty (PhD, Pennsylvania State University) is an associate professor of marketing, Terry College of Business, University of Georgia.
Jian Yang (PhD, University of California, Davis) is a senior director of research, Verizon Media.

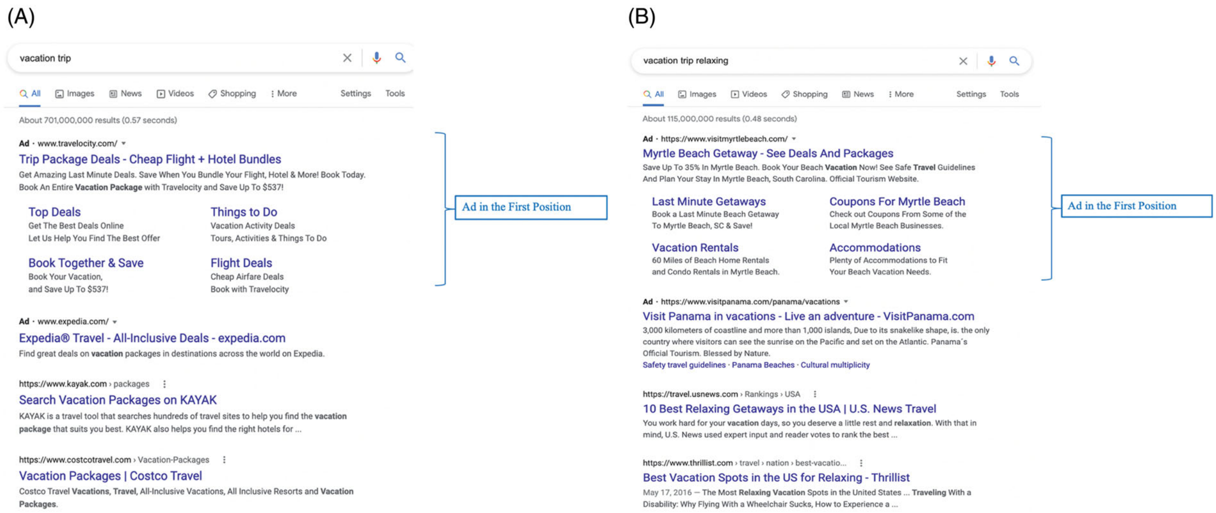

Figure 1. Illustration of search query and the generated text ads: (A) example with no emotion word in search query; (B) example with emotion in search query.

(Figure 1A) to have a significantly different CTR than in the query without the emotion word (Figure 1B)?

A related enquiry is whether CTRs of an ad should depend on the congruency between the emotion word in the search query and any emotion word contained in the corresponding ad. After all, ads, too, might contain emotion words in their texts and traditional advertising research demonstrates that emotional content of ads influence consumers' processing of such ads (Rossiter and Thornton 2004). Thus, we ask, to what extent should the emotion expressed as emotion word(s) in the search query be aligned with the emotion expressed as emotion word(s) in the ad text to stimulate a user to click on the ad?

Related to the two research questions as stated above, we recognize that the presence/absence of an emotion word in search query, as well as the congruency between emotion word(s) in search query and ad, might be contingent on the specific valence of emotion. Multiple behavioral studies about the effect of emotions on consumer actions show that positively valenced emotions have significantly different effects on consumer actions than negatively valenced emotions. As a result, consumer-behavior scholars typically divide emotions into positive or negative valence in order to summarize the range of emotions experienced in the consumption process (see Laros and Steenkamp 2005 for a review). Positively valenced emotions refer to all emotions that give a sense of pleasure such as happiness. In fact, Richins (1997) validates 10 different types of emotions that comprise commonly felt emotions of pleasure by consumers as they pass through stages of the purchase funnel. These emotion types include romantic love, eagerness, love, peacefulness, contentment, optimism, joy, excitement, pride, and relief. Negatively valenced emotions refer to all emotions that give a sense of displeasure. Richins (1997) validates nine types of emotions that comprise commonly felt emotions of displeasure as they pass through stages of the purchase funnel. These emotions include anger, discontent, worry, sadness, fear, shame, envy, loneliness, and guilty. It is worth noting that this set of positive and negative emotions is very comprehensive and encompasses all the frequently studied emotions in the consumer-behavior literature (see Kranzbühler et al. 2020 for a meta-analysis).

Thus, overall, we investigate our first research question (i.e., does the presence or absence of emotion word(s) in search queries matter for ad CTRs) by (1) not differentiating between types of emotions and (2) estimating effects of positively valenced and negatively valenced emotions separately. Similarly, we investigate our second research question (i.e., does the congruency between emotion word(s) in search query and ad text matter for ad CTRs) by estimating effects of congruency (1) without differentiating between types of emotions and (2) separately for positively valenced and negatively valenced emotions. We use a large-scale search-advertising data set from a leading search engine based in the United States. With the use of simple regression techniques and controlling for the relevance of the ad to the search query, we do find that the presence of emotion words in search queries has a significant, non-spurious correlation with ad CTRs.

With our research, we make two specific contributions. First, we emphasize that extant research on emotions in advertising largely focuses on the emotion content of visual and print ads, and their impact on consumers' attitudes and purchase behaviors (Brown, Homer, and Inman 1998, Pham et al. 2001). Unlike prior research, we study the emotion content of both the context within which a consumer views an ad (i.e., search query) and the ad itself. As seen in Figure 1, text ads are typically placed along with organic search results in a web page. Thus, there is a lot of information clutter that a user is exposed to that does not guarantee attention (and clicks) toward a specific ad. This setting is unlike traditional experimental research contexts, in which consumers view ads by default and the research interest is typically in the emotional content of the ad rather than the context within which the ad is viewed. We show that the context is important because emotions expressed in the search process might explain some variation in why an ad gets clicks versus not. Second, in the digital advertising context, the role of emotion words in the search query is not obvious. Whether and what type of emotions expressed by the user in a search query will direct the user's attention to an ad out of the all the information clutter in the web page is thus an empirical question that we seek to address in our research.

Relevance of Emotions in Search Queries

Our interest in emotion words stems from the fact that many search queries might include searches for hedonic products that consumers are interested in. Hedonic products are experiential and are directly associated with consumer emotions (Alba and Williams 2013). There is a lot of theoretical evidence in the literature supporting the premise that both the anticipation of acquiring hedonic products and the acquisition of hedonic products are associated with emotions (Chitturi, Raghunathan, and Mahajan 2008). For instance, merely reading emotional descriptions of a hedonic product that individuals are interested in led to significantly more favorable attitudes of the product than similar descriptions of utilitarian products of interest (Kronrod and Danziger 2013). Individuals are also reported to feel positive and negative emotions when they were successful or unsuccessful in acquiring hedonic products, respectively. Such emotions were not observed for utilitarian products (Chitturi, Raghunathan, and Mahajan 2008). There is substantial research on how consumers tend to seek as well as anticipate emotions that will be derived from consuming products with hedonic attributes (MacInnis, Patrick, and Whan Park 2017).

We extrapolate the established associations between emotions and hedonic products to the context of search queries in the following manner. Research suggests that consumers use keywords to describe the product they search for, such as brand names (Rutz and Bucklin 2011), gender-related terms (Mukherjee and Jansen (2014), and detailed functional attributes (e.g., financial services, organic food; Rutz, Trusov, and Bucklin 2011), or deal-seeking attributes such as price (Im et al. 2016). Although prior keyword research on search queries has not specifically examined hedonic products, we contend that search queries for hedonic products might comprise words that describe emotions that consumers associate with such products.

In order to substantiate our contention, we obtain a random sample of around 110,000 search query-ad pairs from a search-engine platform and identify the search queries with emotion words (we describe our data in detail later). With a dictionary of emotion words (described later), we match the search queries with the emotion-word dictionary and find that 24% of the search queries contain emotion words. Within such search queries, around 58% contains positive emotion words and 41% contains negative emotion words (see Table 1). The analysis thus confirms our contention that emotion words are indeed used in search queries. Further, we used two linguistic experts hired from a freelancing web site to independently

Table 1. Examples of emotion words in our dictionary.

Negative Emotions and Illustrative Emotion Words		Positive Emotions and Illustrative Emotion Words	
Anger	e.g., rage, mad, furious	Love	e.g., affectionate, beloved, friendly
Discontent	e.g., awful, unfulfilled, displeasure	Peacefulness	e.g., relaxing, calm, restful
Worry	e.g., bothered, anxious, concerned	Contentment	e.g., satisfied, fulfilling, ideal
Sadness	e.g., dejected, downhearted, depressed	Optimism	e.g., cheery, encouraging, upbeat
Fear	e.g., nervous, scared, frightened	Joy	e.g., glad, happy, jolly
Shame	e.g., embarrassing, humiliate, abashed	Excitement	e.g., enthusiasm, thrilled, impassionate
Envy	e.g., green-eyed, jealous, envious	Proud	e.g., pride, impressive, congratulations
Loneliness	e.g., solitary, alone, homesick	Relieved	e.g., ease, assured, reassure
Guilty	e.g., regret, sorry, conscience-stricken	Eager	e.g., keen, hopeful, desirous
		Romantic Love	e.g., alluring, amorous, romance

Table 2. Illustrative search queries that include emotion words.

- Peaceful wallpaper
- Peaceful Christian music
- Inspiring homes
- Calming music kids
- Encouraging quotes children
- Encouraging poems
- Encouraging words faith
- Job interview practice nervous
- Sad songs
- Pleasant piano music
- Scary costumes
- Romantic couples massage
- Romantic cards
- Romantic hotels Chicago
- Calming support cat
- Uplifting yoga online
- Thrilling views cabin rentals
- Happy Valentine's day images
- Happy Easter clipart
- Anxious patient therapist
- Nostalgic song
- Gift idea for your loved one
- Exciting greeting card
- Exciting vacation trips

assess each search query that contains an emotion word to identify the product associated with the emotion word in the search query. With a high intercoder reliability (Krippendorff's alpha >.85), we find that 98% of the queries described an experiential or hedonic product or service. In Table 2, we provide an illustrative sample of such queries.

Overall, the above analyses establish that positive and negative emotion words can indeed occur in search queries, especially in searches related to hedonic products or services. Our interest in the rest of the article is to understand if these emotion words can be considered as keywords by advertisers. In order to do so, we want to understand whether the presence of emotion words (whether positively or negatively valenced) in a search query can influence clicks on sponsored ads that are displayed upon the search query. In the next section, we discuss relevant emotion-based theories that might help understand why consumers who use emotion words in searches for products and services might be likely to click on sponsored ads (we assume based on the above analysis that products and services meaningful in our study are mostly hedonic in nature). Following the theoretical exposition, we present our methodology and analysis.

Relevant Emotion-Based Theories

We elaborate on relevant emotion-based theories of information processing in order to demonstrate the theoretical relevance of considering emotions as keywords in search queries.

Theories and Hypotheses

When a search query is activated, in response, the search engine will typically display organic search results as well as text ads. In the search-query result page, organic search results represent non-sponsored links that represent more credible and trusted information as compared to ads[4] (Hotchkiss et al. 2005). Following this logic, ads then represent "extra" information for the user that she attends to only if she is willing to look for information variety (i.e., information beyond organic search results) and, of course, the relevance of the ad to the product/service mentioned in the search query matters. If we control for ad relevance, we are then investigating how emotion words of the individual as expressed in the search query influences the individual's willingness to look through the information clutter or, in other words, seek information variety. To understand the above question, we consider theories that help explain how emotions influence information seeking in individuals. In particular, two specific theories, i.e., affect-as-information and affect as means of self-regulation theories, are appropriate. Both the theories argue for relative effects of positive and negative emotions instead of discussing the effects of the mere presence of emotions. As a result, for our a priori expectations, we are only able to consider effects of positive and negative emotion words in search queries (this is a component of research question 1) as well as effects of congruency between emotion words in the search query and ad (this is research question 2). We are unable to theorize possible effects of the mere presence versus absence of emotion words in search queries. The latter, which is a component of research question 1, is thus subject to only empirical enquiry.

The affect-as-information theory proposes that positive emotions may incentivize individuals to engage in more casual processing of information rather than effortful, systematic processing of information. Negative emotions motivate individuals to do the opposite. Positive feelings elicit a sense of confidence about the self, which reduces the motivation to exert effort to process information; instead, it makes individuals comfortable with casual processing. In contrast, negative feelings induce a sense of doubt about the self that encourages individuals to expend effort to process information in a detailed manner. Correspondingly, studies show that relying on less effortful processing due to positive emotions frees up people's mental resources, which they can then devote to seeking or processing information variety (e.g., Aspinwall 1998; Fredrickson 2000; Isen 1987, 1999).

In contrast, more effortful, in-depth information processing due to negative emotions uses up mental resources, due to which people are unable to seek or process information variety. Further, as less effortful processing requires much fewer mental resources, people experiencing positive (relative to negative) emotions are able to better approach novel objects and stimuli (Cacioppo, Gardner, and Berntson 1999). Indeed, studies indicate that positive emotions encourage cognitive flexibility and creative problem-solving ability because individuals can process varied information efficiently using information cues rather than elaborating every detail of every piece of information. Negative emotions, in contrast, improve the depth of processing and reduce susceptibility to cues and signals (Schwarz, Bless, and Bohner 1991). In sum, positive emotions relative to negative emotions make an individual more likely to approach varied stimuli. Extrapolated to our context, affect-as-information literature suggests that individuals with positive relative to negative emotions (as expressed in their search queries) are more likely to attend to the variety of results upon a search query, thereby being more likely to click on an ad.

Therefore, we expect the following:

> **Hypothesis 1:** Positive emotion words in search queries are more likely to be associated with ad clicks than negative emotion words in search queries.

Unlike the affect-as-information theory, the other major information processing theory, i.e., affect as means of self-regulation theory, provides guidance about the relationship between positive and negative emotions and the likelihood of seeking information with specific embedded emotions. The major tenet of the theory is that individuals expressing positive emotions tend to approach information that helps them protect their positive emotional state, whereas people expressing negative emotions are predisposed to approach information that may improve their emotional state (Erber, Wegner, and Therriault 1996). Emotional states tend to stimulate action tendencies (Lazarus 1991) such that individuals may approach or avoid information based on the emotion-lifting or emotion-threatening tone of the information (Cacioppo, Gardner, and Berntson 1999). When extrapolated to our research context, the theory suggests that emotion words (whether positive or negative) as expressed in a search query might influence actions such as approaching or avoiding an ad. The individual expressing emotion with a positive emotion word in a search query should approach (avoid) ads if the individual anticipates that the ad will help to retain (threaten) the positive state, i.e., corresponding to ads with positive (negative) emotion words. Individuals expressing a negative emotion word are likely to approach (avoid) ads if the individual anticipates that the ad will lift (retain) their negative state, i.e., corresponding to ads with positive (negative) emotion words. In summary, affect as means of self-regulation theory suggests that search queries with positive or negative emotion words are more likely to be associated with clicks of ads that include positive emotion words rather than negative emotion words. Thus, we hypothesize,

> **Hypothesis 2:** Both positive and negative emotion words in search queries are more likely to be associated with ad clicks when the ad contains positive rather than negative emotion words.

Data and Methodology

Data Description

We obtained a large-scale search engine advertising data set from a leading search engine based in the United States, which hosts a search engine and posts sponsored search ads. The data includes the search traffic in the United States for eight consecutive weeks in March and April 2018 with no major holidays. For sponsored search ads, the search engine provides a self-serve, advertiser-facing campaign management system for advertisers to set up and manage ad campaigns. The company also conducts search ad serving (i.e., the process of delivering ads to web-site viewers) with its own system. Hence, the data involved in our analysis, including CTR, query text, ad text (ad headline, description lines, and URL combined), and the various control variables as specified later, are directly observed by the collaborating company. The data set includes search query–ad pairs and their corresponding CTR, wherein the text of search query and text of ad are available. If we include all ads generated on the first web page of a search result, we have a problem related to ad ranking. The higher the ad is placed (i.e., ranked) on the web page, the more relevant might be the advertised product to the search. Higher ad ranks also may correlate with the quality of the advertised product or the strategy of the advertiser. In order to avoid our results being confounded by greater ad relevance and advertiser quality (as signaled by ranking), we include only search query–ad pairs where the ad is in the first position or rank on the search-result web page. For example, in Figure 1, we see a text ad on top of the search page; there are no other ads before it. This would comprise an ad in the first position or rank on a search-result web page. The final data set contains around 110,000 pairs of search query–ad pairs, involving around 2,100 advertisers from 28 industries.

What Kind of Variables Do We Need to Measure?

Our research goal is to estimate relationships among emotion words of search queries, emotion words in ad texts, and CTRs of ads. Our dependent variable of interest is the CTRs of ads generated upon a search query. In order to answer our first research question about whether the presence or absence of emotion words in search queries influence ad CTRs, as a first step we need to identify emotion words in search queries. Second, in order to understand if the effect of emotion words in search queries is contingent on the type of emotion depicted in the emotion word, we need to classify emotion words as positively valenced and negatively valenced. In order to answer our second research question about congruency between emotion words in search query and ad, we need to follow the same steps as before for ads.

Identification of Emotion Words

To obtain a dictionary of emotion words, we start with all the emotion words described in Richins (1997). Scholars studying the role of emotions in consumption consider Richins (1997) to provide a comprehensive set of emotions that individuals may feel in the consumption process (e.g., Bagozzi, Gopinath, and Nyer 1999). We used a panel of two experts in consumer-behavior research to classify these basic emotion words in Richins (1997) as positively valenced or negatively valenced. This technique allowed us to revalidate whether the range of positively valenced emotion words as suggested by Richins (1997) indeed were perceived as positively valenced. Similarly, this technique allowed us to confirm whether the emotion words representing the range of negatively valenced emotions as suggested by Richins (1997) were indeed perceived as negatively valenced. There was 100% agreement between the two experts. The emotion words depicting "surprise" in Richins (1997) was considered neither positive nor negative and we have less than 0.2% queries in our data set with such emotion; hence, we combine it with observations that do not include emotion words.

Then, we manually expanded the emotion words given in Richins (1997) using synonyms (for example "angry" expanding to "furious") and grammatical variations (for example "worry" expanding to "worrying"), and hence obtain a basic dictionary for emotions of positive and negative valence.

To obtain more variations from real search queries, we further embed the emotion words into a vector space by the word-embedding technique and find their neighbors in the embedding space to add into the word collection. This approach leverages distributed language models (Mikolov et al. 2013; Turian, Ratinov, and Bengio 2010) that have been employed in natural language processing (NLP) applications. It studies sequences of words and learns word representation in a continuous vector space, i.e., it represents each word with a vector of numbers. In the learned-embedding vector space, words that are semantically similar will be close to each other (Mikolov et al. 2013). After embedding the words with vectors, we expand the dictionary of emotion words by looking for the nearest neighbors of the words in the manually crafted basic dictionary. We then had three independent linguistic experts assess each emotion word in the dictionary and deliberate whether the word indeed represents an emotion. Through this deliberation process (with a high average pairwise inter-coder reliability: Krippendorff's alpha $> .85$), we arrived at a final emotion word list of 810 words including both positive and negative emotions. In Table 1, we provide an illustrative list of positive and negative emotions and a few examples of words that represent that emotion type. [5]

With this developed dictionary of 810 emotion words, we matched the emotion words to search queries and ads, and thus are able to not only identify whether emotion words are present or absent in every search query–ad pair and are also able to classify the words as positive or negative valence. We provide descriptive information about the proportions of emotion categories in our data set in Table 3.

Measures of Dependent Variable and Control Variables

In this research, our metric of the effect of emotion words is CTR of the ad in a search query-ad pair. The CTR of an ad is defined as the ratio of the number of ad clicks and the number of ad impressions. We utilize the CTR for each pair of search query and ad as the dependent variable, and investigate its relationship with emotion words identified in search queries and ad texts.

We need to control for factors that may impact the CTR of ads that have been identified in the literature (e.g., Atkinson, Driesener, and Corkindale 2014) as follows. (1) We need to account for the presence of

Table 3. Descriptive statistics of data set.

Search queries having positive emotion word: 58%		Search queries having negative emotion word: 41%		Search queries with emotion words that are neutral:* 1%
Corresponding ads with positive emotion word: 46%	Corresponding ads with negative emotion word: 9.5%	Corresponding ads with positive emotion word: 34%	Corresponding ads with negative emotion word: 13%	

Notes. Ninety-eight percent of search queries with emotion words include hedonic products and services
Total number of search query–ad pairs in data set: 110,000.
Search queries that include emotion words: 24%
*Emotion words depicting "surprise" are considered neither positive nor negative in Richins (1997), and we have less than 0.2% queries in our overall data set with such emotion words, and hence we combine it with the cases of no or absence of emotion word.

emotion words in the ad text (Rossiter and Thornton 2004). (2) Though we only use first-ranked ads, we do need to control for the degree of the relevance of the ad to the search query. We use the quality scores of the ad in a query–ad pair as a control variable. Quality scores are calculated by most search engines and, in general, ads with greater quality scores are considered better matched to the consumer's needs as expressed in the search query (Nabout and Skiera 2012). Quality score partially depends on the type of keyword that is bid upon by advertisers. Quality scores are higher for keywords that signal high intention. These high-intention keywords are typically selected from the following: specific product, specific product category, and finally words that are associated with best, cheap, comparisons, and reviews.[6] In our review of high-intention keywords, we do not find any mention of emotion words. Thus, to our knowledge, the ad quality score does not account for emotion words. (3) We control for the presence of words in queries and ad texts that express functional attributes of a product such as durability, etc. (Bulut 2015). (4) We control for the presence of brand names in the queries and ad texts because studies have shown that ads are likely to get clicks if they are matched to search queries in terms of brand names (Rutz and Bucklin 2012). (5) We control for the length of the search query (i.e., number of words) because long versus short search queries represent high versus low specificity of information requested in the search (Hafernik and Jansen 2013). (6) We control for the presence of extensions in the ad. Ad extensions include formats such as call buttons and links to specific parts of the landing page that increase the space occupied by the ad and thus the visibility of the ad in the search results page. (7) We control for the bid price of each ad because the advertisers may employ different bid prices. (8) We also include the brand fixed effects of the advertised products (around 63% of the brands changed their advertising content during the time period and hence the data provide enough variations after controlling for brands).

Method

We use the regression method to estimate effects of emotion words for ad CTRs. We address our research questions sequentially using different regression equations as follows.

For Research Question 1

For our first research question about the effect of the presence/absence of emotion words in search queries, we follow the two equations below in sequence.

- In a query-ad pair i, for effect of presence/absence of any emotion word (regardless of emotion valence) in the query, we use the following equation:

$$\begin{aligned} Ad\ CTR_i = \beta_0 &+ \beta_1 QueryHasEmotion_i \\ &+ \beta_2 AdHasEmotion_i \\ &+ Control\ Variables_i + \varepsilon_i, \end{aligned} \tag{1}$$

Where $Ad\ CTR_i$ is the CTR of the ad in the ith query–ad pair, *QueryHasEmotion* is a dummy variable indicating presence (1)/absence (0) of an emotion word in the query in the ith query-ad pair, and *AdHasEmotion* is a dummy variable indicating presence (1)/absence (0) of an emotion word in the ad in the ith query-ad pair. *Control Va* capture the control variables discussed earlier, and ε_i is the random error term. If the coefficient estimate β_1 is positive and statistically significant, this will suggest that the presence of emotion word in search queries probably lifts the CTR of ads.

- In order to test H1, in a query-ad pair i, for separate effects of presence of positively valenced emotion word in query and negatively valenced emotion word in query, we use the following equation:

$$\begin{aligned} Ad\ CTR_i = \beta_0 &+ \beta_1 QueryPosEmotion_i \\ &+ \beta_2 QueryNegEmotion_i \\ &+ \beta_3 AdPosEmotion_i \\ &+ \beta_4 AdNegEmotion_i \\ &+ Control\ Variables_i + \varepsilon_i, \end{aligned} \tag{2}$$

Where *QueryPosEmotion* is a dummy variable indicating presence (1)/absence (0) of a positively valenced emotion word in the query in the ith query-ad pair and *QueryNegEmotion* is a dummy variable indicating presence (1)/absence (0) of a negatively valenced emotion word in the query in the ith queryad pair. *AdPosEmotion* is a dummy variable indicating presence (1)/absence(0) of a positive valence emotion word in the ad in the ith query-ad pair, and *AdNegEmotion* is a dummy variable indicating presence (1)/absence(0) of a negative valence emotion word in the ad in the ith query-ad pair. We note that the dummy variables do not cause a collinearity problem. For example, absence of a positive valence word does not imply presence of negative emotion word. Instead, absence of positive valence word includes observations with negative emotion word as well as those without any emotion word at all. The rest of the variables are similar to those in Equation 1. If the coefficient estimate β_1 is positive and statistically significant, it will suggest that the presence of positively valenced emotion words in search queries lifts the CTR of ads. Similarly, if the coefficient estimate β_2 is positive and statistically significant, it suggests that the presence of negative valence emotion words in search queries lifts the CTR of ads. We can then compare the two coefficients to assess the relative effects of positively and negatively valenced emotion words.

For Research Question 2

For our second research question about the effect of the congruency between emotion words in search queries and ads in a query-ad pair, we follow the equations below in sequence.

- First, in order to assess if congruency between emotion words in search query and ad matters at a broad level, we directly access the interaction effect of existence of emotion word in query and ad, with the following equation:

$$\begin{aligned} Ad\ CTR_i = \beta_0 &+ \beta_1\ QueryHasEmotion_i \\ &\times AdHasEmotion_i \\ &+ \beta_2 QueryHasEmotion_i \\ &+ \beta_3 AdHasEmotion_i \\ &+ Control\ Variables_i + \varepsilon_i, \end{aligned} \tag{3}$$

And hence the coefficient β_1 represents the interaction effect of existence of emotion in query and ad.

Next, in order to test H2 directly, we open up the interaction to include different combinations of positive and negative emotion words in the query-ad pair as follows,

$$\begin{aligned} Ad\ CTR_i = \beta_0 &+ \varphi_1 QueryPosEmotion_i \\ &\times AdPosEmotion_i + \varphi_2 QueryPosEmotion_i \\ &\times AdNegEmotion_i + \varphi_3 QueryNegEmotion_i \\ &\times AdPosEmotion_i + \varphi_4 QueryNegEmotion_i \\ &\times AdNegEmotion_i + \beta_1 QueryPosEmotion_i \\ &+ \beta_2 QueryNegEmotion_i + \beta_3 AdPosEmotion_i \\ &+ \beta_4 AdNegEmotion_i + Control\ Variables_i + \varepsilon_i, \end{aligned} \tag{4}$$

And hence the coefficients φ_1, φ_2, φ_3 and φ_4 represent the interaction effect of positive emotion in both query and ad, positive emotion in query while negative emotion in ad, negative emotion in query while positive emotion in ad, and negative emotion in both query and ad, respectively.

Results

In our data, each observed dependent variable is CTR of a set of ad impressions. Since the ad traffic volumes for different ads or queries vary, each observed CTR covers a different amount of impressions. Hence, we weigh each observation with its corresponding number of impressions when we estimate the regression models.

We organize the results section by discussing the results of the equations sequentially.

Results for Research Question 1: Effect of Presence of Emotion Word in Search Query

For the effect of the presence of any emotion word in search query on ad CTR, we estimate Equation 1 and present results in Table 4. In column 2, we show the results with an emotion word in the search query incorporated in the model. The effect of the presence of emotion word in search query is positive and significant ($b = .0011$, $p < .01$), suggesting that the

Table 4. Effects of emotion words on ad CTR.

1	2 Model with Emotion Word in Search Query Equation 1	3 Model with Interaction of Emotion Words in Search Query and Ad Equation 3
Interaction of presence of emotion word in search query and ad		.00076*** (.00026)
Presence of emotion word in search query	.0011*** (8.2e–05)	.00098*** (.00015)
Presence of emotion word in ad	.00034*** (.00014)	.00033** (.00015)
Quality score of ad	.32*** (7.3e–05)	.33*** (7.4e–05)
Functional attribute in ad	.0014*** (.00012)	.0013*** (.00012)
Brand name in ad	.00030** (.00016)	.00030** (.00015)
Functional attribute in search query	.0011*** (.00040)	.0011** (.00039)
Brand name in search query	.0014*** (.00016)	.0014*** (.00016)
Query length	7.5e–05** (3.4e–05)	7.6e–05** (3.3e–05)
Ad extension	.00023*** (7.8e–05)	.00024*** (7.8e–05)
Bid price	3.7e–05*** (1.9e–05)	3.8e–05*** (1.9e–05)
Brand fixed effects	Included	Included
R-sq	0.788	0.791

***$p < .01$, **$p < .05$.

Table 5. Effects of emotion words of positive and negative valence on ad CTR.

1	2 Model With Emotion Word in Search Query Equation 2	3 Model with Interaction of Emotion Words in Query and Ad Equation 4
Interaction of positive emotion in both query and ad		0.0018*** (0.00024)
Interaction of positive emotion in query and negative emotion in ad		−0.0014*** (0.00048)
Interaction of negative emotion in both query and ad		−0.0011*** (0.00040)
Interaction of negative emotion in query and positive emotion in ad		0.00059** (0.00029)
Presence of emotion word of positive valence in search query	.0013*** (.00011)	.0012*** (2.0e– 04)
Presence of emotion word of negative valence in search query	.00068*** (.00013)	.00094*** (.00023)
Presence of emotion word of positive valence in Ad	.00042*** (.00016)	.00037** (.00017)
Presence of emotion word of negative valence in ad	.00012 (.00022)	.00018 (.00024)
Quality score of ad	.32*** (7.4e–05)	.33*** (7.4e–05)
Functional attribute in ad	.0014*** (.00012)	.0014*** (.00012)
Brand name in ad	.00028** (.00016)	.00030** (.00015)
Functional attribute in search query	.0010** (.00040)	.00097** (.00039)
Brand name in search query	.0014*** (.00016)	.0015*** (1.6e–04)
Query length	7.0e–05** (3.4e–05)	7.1e–05** (3.3e–05)
Ad extension	.00023*** (7.8e–05)	.00022*** (7.8e–05)
Bid Price	3.8e–05** (1.9e–05)	3.7e–05* (1.9e–05)
Brand fixed effects	Included	Included
R-sq	0.790	0.794

***$p < .01$, **$p < .05$, *$p < .10$.

presence of an emotion word in the search query links to higher ad CTRs. For the separate effects of positive valence and negative valence emotion words in the search query, we estimate Equation 2 and present results in column 2 of Table 5. The effect of the presence of a positive valence emotion word in the search query has a positive and significant influence on ad CTR ($b = .0013$, $p < .01$). The effect of the presence of a negative valence emotion word in search query is positive and significant as well ($b = .00068$, $p < .01$). Thus, our results suggest that, though the effect of both types of emotion word is significant, the presence of positive (relative to negative) emotion word in search query links to higher ad CTR due to greater effect size ($p < .01$). It confirms our Hypothesis 1, that positive emotion words in search queries are more likely to be associated with ad clicks than negative emotion words in search queries.

Results for Research Question 2: Effect of Congruency between Emotion Words in Search Query and Ad

For the effect of congruency between emotion words in search query and ad without distinguishing between emotion valence, we estimate Equation 3 and present results in column 3 of Table 4. We find that congruency does matter, i.e., the coefficient of the interaction of the presence of emotion words in query and ad is positive and significant ($b = .00076$, $p < .01$), showing that the presence of an emotion word in both search and ad links to higher ad CTR.[7]

For the model with separate effects of congruency in terms of positive valence and negative valence, we estimate Equation 4 and show the results in column 3 of Table 5. When the emotion words in query is positive, if the emotion words in ad is also positive, the coefficient of the interaction is positive and significant ($b = .0018$, $p < .01$). However, when emotion words in query is negative, if the emotion words in ad is also negative, the coefficient of the interaction is negative and significant ($b = -.0011$, $p < .01$). Hence the presence of same valence of emotion words in query and ad improves CTR only in the case of positive valence. Also, when the emotion words in query is negative, if the emotion words in ad is positive, the coefficient of the interaction is positive and significant ($b = .00059$, $p < .05$); when the emotion words in query is positive, if the emotion words in ad is negative, the coefficient of the interaction is negative and significant ($b = -.0014$, $p < .05$). Hence, both positive and negative emotion words in search queries are more likely to be positively associated with ad clicks when the ad contains positive rather than negative emotion words, which confirms Hypothesis 2.

Discussion

In response to calls to enhance advertising effectiveness in the digital space, we investigate the context of search queries and sponsored text ads. We study if the CTRs of sponsored ads are influenced by emotion words in search queries, and the congruency of emotion words in the search query and ad. We add to marketing research on digital advertising targeting in which relevance of the product/service advertised to the search query is considered important (e.g., Bleier and Eisenbeiss (2015) and He and Chen 2006). Upon empirically controlling for factors that improve the relevance of the ad (see Schlangenotto, Poniatowski, and Kundisch 2018 for a review), we find that the presence of emotion words as well as the valence of emotion words within the query-ad combination are significantly associated with the CTRs of ads. Although our results are based on simple regression estimates of observational data, they do at least suggest that the emotion content of search queries has a nontrivial association with CTRs of ads, and therefore might matter while matching ads to search queries for hedonic products and services. In particular, we find that emotion words of positive valence in the search query perhaps should be congruent, i.e., paired with emotion words of positive valence in ads. In contrast, emotion words of negative valence in the search query should not be paired with emotion words of negative valence in ads. Instead, emotional words of negative valence in the search query should perhaps be paired with emotion words of positive valence in ads.

In traditional advertising research, scholars have shown that emotions are relevant. However, research on emotions in advertising largely focuses on the emotion content of visual and print ads, and their impact on consumers' attitudes and purchase behaviors (Brown, Homer, and Inman 1998, Pham et al. 2001). Unlike traditional advertising research, we show that in the digital domain, the relevance of the emotion content of the context within which an ad is viewed is also important. To our knowledge, our research is the first to consider the role of emotions as stimuli embedded within the digital environment. Our categorization of emotions within search queries and ads and their combined effectiveness for CTRs represents a first attempt at understanding how emotions embedded in content outside of the ad are useful.

Discussion of Effect Sizes of Emotion Words

Although the analysis is largely correlational in nature, in our results, we find that the effect size of emotion words is small compared to some other variables, especially the quality score. Quality score is assigned by the algorithms of the search-engine platform that captures the relevance of the ad and query, and is one of the most important factors for effective search advertising (Nabout and Skiera 2012). It has a very large effect size ($b = .33$) compared to emotion congruency in query and ad ($b = .00076$), and a "back-of-envelope" estimate in footnote 7 suggests that emotion congruency has a marginally incremental effect compared to the effect of quality score. We wanted to understand if the low effect size of emotion congruency is a result of the fact that quality score might include some consideration of emotion words, which then substantially reduces the effect of emotion words when it is considered as a variable separate from quality score. In our reviews of various ad blogs as well as Google AdWords platform, we find that though keywords are given consideration in the quality score, emotion words do not seem to comprise these keywords. Instead, other keywords such as those indicating high purchase intention, such as deals, promotions, affordability, comparisons, reviews, etc., are considered.[8] Considering the importance of quality score and the amount of purchase-intention information it may have covered, our analysis suggests that the impact of emotion congruency is still substantial in addition to quality score.

Also, we have controlled for several other important features related to ad performance in our models, such as the functional attribute of a product or service, presence of brand names, and keyword length, all of which have been the subject of much study in the domain of sponsored ads (e.g., Hafernik and Jansen 2013; Jerath, Ma, and Park 2014; Zhang et al. 2014; Rutz and Trusov 2011). We still observe a significant impact of emotion words after controlling for these factors. Compared to these keyword possibilities studied in the literature, to our knowledge this is the only study to raise the possibility that emotion words might also be used as keywords by advertisers for more effective search advertising of hedonic products and services.

Limitations and Future Research

Our study calls for future research in multiple aspects of digital advertising. Though our dependent variable of interest is CTR, future research needs to go a step further and understand the implications of the emotion content of the landing page. The landing page is the advertiser's web site that is displayed when a user clicks on a sponsored ad. The effectiveness of emotion content of search queries in combination with or relative to the emotion content of the ad text and landing page needs to be explored. Following the paid-search literature, our study provides implications for individual ads, and future research may further study the implications for advertisers in terms of competitive advantage. For example, though we believe that our results hold largely for search queries including hedonic products and services, future research may study specific categories of hedonic products and services in order to understand more fine-grained effects of emotion words.

Notes

1. Available at www.statista.com/ statistics/237974/online-advertising-spending-worldwide/#:∼:text=It%20was%20calculated%20that%20the, 389%20billion% 20dollars%20in%202021.
2. Available at https://digitalfireflymarketing.com/our-blog/search-engine-optimization-pay-per-click-importance/#:∼:text=Paid%20search%20results%20gain%201.5,track%20ROI%20and%20manage%20budgets.
3. Available at https://valveandmeter.com/ pay-per-click-statistics/.
4. Available at https://www.zerolimitweb.com/organic-vs-ppc-2018- ctr-results-best-practices/.
5. The emotion word dictionary is available online at www.dropbox.com/s/7xwgfy6cmqwio6x/emotion_word_onlineAppendix.xlsx?dl=0. Also, see the Appendix for details about mining emotion words using the word embedding technique.
6. Available at www.wordstream.com/keyword-intent.
7. To give the audience a sense of the scale of the impact of emotion congruency, we did a rough comparison of the impact of emotion congruency and the impact of ad quality score. Specifically, we create a binary variable *AdQuality_binary*, where 1 indicates high ad quality score and 0 indicates low ad quality score, and the high/low ad quality is split at the median of ad quality scores. Similarly, we create a binary variable *Congruence_binary*, where 1 indicates high emotion congruence and 0 indicates low emotion congruence, and the high/low congruence is split at the median of the cosine similarity between the word embedding vectors of the emotion words in query and ad in each query-ad pair (when emotion words do exist in both query and ad). Cosine similarity represents the congruency between emotion words in the query and ad, and provides a continuous variable where higher levels indicate higher congruency or sematic similarity and lower levels indicate lower congruency or semantic similarity. Only for this specific analysis in this footnote, we measure congruency between emotion words in query and ad using the cosine similarity technique. We then fit the following model: $Ad\ CTR_i = \beta_0 = \beta_1 Congruence\_binary_i + \beta_2 AdQuality\_binary_i + \beta_3 QueryHasEmotion_i + \beta_4 AdHasEmotion_i + OtherControlVariables_i + \gamma_1 CongruencyExist_i + .$
   There can be a confound in the interpretation of the estimate of *Congruence_binary* (β_1) because the value of 0 in the measure of *Congruence_binary* includes observations with absence of emotion words, i.e., due to the absence of emotion words in both query and ad or absence of emotion word in only query or absence of emotion word in only ad. In order to control for this issue, we include a dummy variable *CongruencyExist*, which captures the presence of emotion words in both ad and query in the ith query-ad pair. Hence the coefficients of *AdQuality_binary* and *Congruence_binary* represent the scale of the impact on CTR of ad quality score and emotion congruency, respectively. The coefficients for both variables are significant with $p < .01$. The coefficient for *AdQuality_binary* is 0.031, while the coefficient for *Congruence_binary* is 0.0017. The coefficients imply that, by shifting from low emotion congruency to high emotion congruency, the impact on CTR is around 5.5% of the impact when shifting from low ad quality score to high ad quality score. Since the ad quality score is one of the most important factors for effective search advertising (Nabout and Skiera 2012), the analysis suggests that the scale of the impact of emotion congruency is also substantial.
   The goal of this analysis is not to compare the significance of emotion congruency and ad quality. It only serves as a "back-of-envelope" estimate and the main

purpose is to provide suggestive evidence on the scale of the impact of emotion congruency.

8. Available at www.wordstream.com/keyword-intent, https://support.google.com/google-ads/answer/6167118?hl=en.

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Appendix

Procedure for Emotion Dictionary Mining

In this appendix, we illustrate the steps and algorithms employed in the mining of emotion words.

The mining process of search queries follows three major steps:

Step 1: We manually compose a basic list of words mentioned in Richins (1997). We start with each emotion word, e.g., "anger" and "worry," and then manually expand the emotion words with their synonyms (for example "angry" expanding to "furious") and grammatical variations (for example "worry" expanding to "worrying"). This basic list of words serves as the "seed-list," which we could further expand with steps (2) and (3).

Step 2: We mine the search logs and represent each searched word with a vector of real numbers, and this step is often known as "word embedding" (or "word2vec"). The technique is a key feature of language models (Mikolov et al. 2013; Turian, Ratinov, and Bengio 2010), and it has demonstrated success in various tasks such as sentiment classification (available at https://arxiv.org/abs/1408.5882), text topic modeling (Li et al. 2018) and Question&Answer system (Lin and Shen 2017). Specifically, our word embedding procedure is based on the Skip-gram model in Mikolov et al. (2013). The basic idea of the Skip-gram model (Mikolov et al. 2013) is to represent each word with a vector of real numbers, so that the word representations are useful to predict the surrounding words in a word sequence, which is usually defined by a sentence or a document. Formally, given a sequence of words w_1, w_2, w_3 …, w_T, if we represent each word w with a vector v, then the basic Skip-gram model defines $p(w_j|w_i)$ with the corresponding vectors as

$$p(w_j|w_i) = \frac{\exp\left(v'_{w_j} v_{w_i}\right)}{\sum_{h=1}^{H} \exp\left(v'_{w_h} v_{w_i}\right)} \tag{A.1}$$

where H is the number of unique words in the dataset. Then the objective of the models is to maximize the following log probability:

$$\frac{1}{T}\sum\nolimits_{t=-1}^{T} \sum\nolimits_{-c\le j\le c,\ j\ne 0} \log p\left(w_{t+j}|w_t\right) \tag{A.2}$$

where c defines the "surrounding" window. By maximizing the objective function, each word is represented by an embedding vector.

In our context of online search, we worked with the collaborating company to train the text embedding with a proprietary search data set. Specifically, we organized user's search queries into sessions, i.e., uninterrupted sequences of search activities. A new search session is initiated if there is a time gap of more than 30 min between two activities of a user. Concatenating the search queries within each session, we obtain sequences of words. Then, the learning goal is to find an embedding for each word, using the search sessions as sequences of words.

During the training, sessions with a single search query were discarded. The sessions are preprocessed, including removing punctuations, misspellings, and stop words, and then the words are tokenized. We follow the common practice in word-embedding literatures (such as Grbovic et al. 2016), and set the dimensionality of the embedding space to be 300, the window size to be five, and the number of random negative samples per vector update to be five. After the training, we obtain a vector representation for each word in the search log.

Step 3: In this step, we utilize the "seed-list" of emotion words as in step 1, and the vector representation of words as in step 2, to expand our dictionary. Specifically, for each word in the seed-list, we calculate its cosine similarity with the vector representation of other words, and find K "nearest neighbor" words with the largest similarity. We determine K, the number of neighboring words, by a grid search. Specifically, we obtain the dictionary with K equal to 5, 10, 15, and so on. The scale of the dictionary does not increase linearly with K, because, with higher K, it is more likely to obtain repeated words or words that may not pass manual cleaning. We then choose K such that a larger number of neighboring words does not add more words in the final expanded dictionary, and K is set to 30. We also look for neighboring words based on a cut-off value of cosine similarity. Similarly, we determine the cut-off value by a grid search and set the cut-off value such that a lower value does not add more words in the final expanded dictionary in addition to the K nearest neighbors we found as described above. The cut-off value is set at 0.80. To make the dictionary more complete, we also compare our dictionary with the words of "affective processes" categories in the Linguistic Inquiry and Word Count (LIWC) 2015 dictionary (available at https://repositories.lib.utexas.edu/bitstream/handle/2152/31333/LIWC2015_LanguageManual.pdf); if a word is covered by LIWC 2015 dictionary, and is included in any query of ad in our data set, and is related to the emotion words in Richins (1997), we also add it into the dictionary.

As a final step, we hired three linguistic experts to assess every word in the dictionary and provide their judgement of whether the word indeed represents an emotion. Through this deliberation process (with a high average pairwise inter-coder reliability: Krippendorff's alpha >.85), we arrived at a final emotion word list of 810 words.