Recommendation for Video Advertisements based on Personality Traits and Companion Content

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ABSTRACT

People encounter video ads every day when they access online content. While ads can be annoying or greeted with resistance, they can also be seen as informative and enjoyable. We asked the question, what might make an ad more enjoyable? And, do people with different personality traits prefer to watch different ads – could it be possible to better match ads and people? To answer these questions, we conducted an online study where we asked people to watch video ads of different emotional sentiments. We also measured their personality traits through an online survey. We found that the sentiment of people's preferred video ads varies significantly based on their personality traits. Additionally, we investigated when these ads are accompanied by content, how the emotional state induced by accompanying content affects people's ad preferences. We found that there was a complex relationship between people's emotional state induced by accompanying content and their ad preference when an ad highlighted either an alertness or calmness sentiment. However, when an ad highlighted activeness and amusement, the relationship was not significant. Overall, our results show that people's personality traits and their emotional states are two key elements that predict the tone of their preferred video ads.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in HCI*.

KEYWORDS

Video ad recommendation, ad sentiments, companion content, advertising

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1 INTRODUCTION

Video ads are one of the most influential media for advertising products to an audience. In the age of social media and online platforms, video ads are integral parts of our daily life. In a recent study, it was found that US agencies and marketers are increasing their budgetary commitments to digital video advertising [21], and by 2018 they were expected to spend nearly 13 billion on video marketing [2]. Advertisements placed on sites or within content provide primary revenue for many content providers, however, because of the large number of ads, the audience may just ignore these ads if they do not find them attractive and relevant. So, it is important to find an alignment between the advertiser and the audience so that the audience can be shown more enjoyable and relevant ads in general, and the content providers can continue to support their content.

Previous work has found that people often try to avoid online ads because of perceived goal impediment, perceived ad clutter, and prior negative experience [15]. However, researchers have also found that in some scenarios, people might welcome some ads because ads provide needed information about products and services. For example, Stevenson and Pasek found that people prefer to watch personalized ads more than non-personalized ads [68].

Many attempts have been made to investigate the factors that determine people's preference for ads. Since the Big-Five personality trait model is considered a stable measure to observe individuals' stable attributes [5], marketing researchers have used it as a tool to model consumers' behavioral traits and long term purchase patterns. For example, researchers have shown that people's personality traits such as openness and neuroticism can predict whether someone will be generally favorable to online ads or not [12]. However, we still do not know what specific type of ads that people prefer. Moreover, although personality traits such as conscientiousness are known to be positively associated with value consciousness [13], it is still not known how Big-Five personality traits such as conscientiousness, extraversion, and agreeableness may influence video ad preference. Since emotional sentiment is considered a strong predictor for successful movies [11], we aimed to investigate the effect of people's personality traits on the sentiment of their preferred video ads. Moreover, online ads are rarely shown on their own; rather they are seen in context, surrounded by content such as news articles or a social media feed. This accompanying content is known as companion content in the ad world. To our knowledge, the emotional state stimulated by the companion content has not been tested in terms of how it interacts with both the audience member and attributes of ads to shape preferences. Similar to contagion of emotional sentiments from social interaction [31], we hypothesized that the emotional state created by companion content might have a significant effect on people's ad preferences.

In this work, we investigated how people with different levels of the five personality traits react to ads highlighting different emotional sentiments. To this end, we utilized an open-source video ad dataset published by Hussain et al. [35]. This pool contains video ads labeled across a wide range of emotional sentiments. We recruited Amazon Mechanical Turkers to conduct an empirical survey study. First, we conducted a survey to determine the personality traits of our participants. Next, we asked them to watch ads from different sentiment categories, and they later reported which one they preferred. This study allowed us to establish a relationship between people's personality traits and the emotional sentiment of their preferred video ads. For example, we found that participants with high extraversion preferred "active" ads whereas participants high in agreeableness preferred "alert" toned ads the most. We discuss active and alert sentiments for video ads in more detail later in the paper.

In addition to trait-level audience preferences, in the second study, we explored whether the emotional state stimulated by companion content could affect the preferred emotional sentiment of video ads. To this end, we repeated all the steps of the first study; however, we added an extra initial step–we asked Turkers to think of a situation when they felt either a strong positive or a strong negative sentiment. The purpose of this thinking task was to replicate an emotional state that people will generally experience by reading an emotionally toned news article or social media post. Right after this thinking task, we asked our participants to repeat the task conducted in the first study. We found that the emotional state only affected the sentiment of people's preferred video ads when the ads highlighted either alertness or calmness. However, for ads highlighting activeness and amusement states, the stimulated emotional state had no significant impact.

This paper makes an important contribution to practice. To our knowledge, for the first time, we have demonstrated the relationship between people's personality traits and the sentiment of their preferred video ads. This work further expands our understanding of the important effect of companion content on people's preferences for ads. We contribute to the IUI community by offering recommendations for video ads aligned with people's natural preferences.

2 RELATED WORK

2.1 Personality trait model

The Big-Five model is a well-established framework for measuring personality traits. The effort to organize the taxonomy of personality began shortly after McDougall [49] claimed that personality could be discerned through the following five distinct factors: intellect, character, temperament, disposition, and temper. Since then several notable efforts have been made to develop a concise personality model [10, 24, 70]. Among them, Norman's work [53] is significant and has been referred to as "Norman's Big Five" or simply as the "Big-Five". Later, an impressive body of research has verified the 5-factor model [19, 27, 48]. Table 1 lists the dominant features of all five personality traits.

The conventional way to determine users' personality traits is to ask people to complete a survey (such as BFI-44) that contains multiple questions related to each trait [38]. However, asking users to complete a long survey is not a practical approach in all scenarios. Recently, attempts have been made to predict personality traits automatically from user-generated data. Prior work showed that data extracted from social media [67] such as Facebook [45], Twitter [60], and Instagram [23] and social network [66] can predict people's personality traits. However, social media and social network data are not the only data source that can predict people's personality traits. People's smartphone usage data, such as the number of outgoing and missed calls, can also predict certain personality traits significantly above chance [14, 18]. Pianesi et al [58] showed that even acoustic and visual features captured from a meeting environment can also predict some personality traits with considerable accuracy. The prospect of determining personality traits automatically inspired researchers to apply personality traits in several domains. We discuss how this Big-Five personality trait model is used in a wide range of domains in the next two sections.

Table 1: The table lists the dominant characteristics of the people with each personality trait.

Traits	Dominant Features
Extraversion	excitability, sociability, talkativeness, assertiveness
Agreeableness	trust, altruism, kindness, affection
Openness	creativity, openness to trying new things, focus on tackling new challenges
Conscientiousness	thoughtfulness, good impulse control, goal-directed behaviors, organized
Neuroticism	sadness, moodiness, emotional instability

2.2 Impact of personality traits in diverse domains

The impact of personality traits has been studied in various settings and outcomes. Barrick et al. [39] studied the effect of personality traits on job-performance criteria and found that people with high conscientiousness perform consistently well across all job groups. Hu et al. [34] found that music recommendations are more effective when they are made based on people's personality traits. Golbeck et al. [26] established a relationship between people's personality traits and movie preference for Netflix users. Landers et al. [42] found that people who are high internet users score low on agreeableness, conscientiousness, and extraversion traits.

Big-Five personality traits were also used to analyze human behavior and mental health conditions. For example, Barlett et al. [4] found that both openness and agreeableness have direct and indirect relationships with physical aggression, but have only an indirect relationship with violent behavior. Similarly, neuroticism has both direct and indirect relationships with physical aggression but not with violent behavior. Kotov et al. [41] found that neuroticism has a strong correlation with anxiety, depression, and substance use disorders. This body of literature shows that personality traits can be effectively related to a wide range of diverse domains. Next, we narrow our focus to advertising and describe how researchers in advertising utilize personality traits to explain advertising phenomena.

2.3 Impact of personality traits in advertising

In the advertising literature, researchers have studied the impact of personality traits because they considered it as a promising tool for optimal marketing. In the context of marketing and advertising, Hirsh et al. [33] found that people respond more positively to a marketing message when the message is tailored to their personality traits. Moreover, prior work has shown that when people spend money on products that fit their personality, they feel more happy and satisfied [47]. Mulyanegara et al. [50] analyzed the relationship between brand personality and personality traits and found that people with conscientiousness prefer trusted brands (brands which are reliable and persevering) whereas high extraversion people prefer sociable brands (brands which are friendly, creative, and outgoing). Picazo-Vela et al. [59] studied the relationship between personality traits and people's attitude toward providing online reviews for products. They found that attitude, perceived pressure, neuroticism, and conscientiousness can reliably predict someone's intention to provide an online review. Chen et al. [12] showed how people's personality traits can be reliably derived from their social media posts and that people with high openness and low neuroticism are generally more favorable to targeted ads sent through social media.

Inspired by this existing line of work, we established a relationship between people's personality traits and the emotional tone of their preferred video ads.

2.4 Impact of companion content

Companion content for an ad can be anything that accompanies the ad. For example, when a video ad appears during an online video, then the main video becomes the companion content of the video ad. The idea that companion content can stimulate viewers' emotions has been previously studied with television advertisements. When advertisers placed commercials during television programs, they did not want to associate themselves with depressing programs because they believed that negative information presented in the TV program might adversely affect the perception and resultant impact of their ads. For example, H. J. Heinz company had a stated policy to avoid programs that were overtly violent because they did not want to associate themselves with negative emotions [22]. Coca-Cola avoided news programs because they believed that negative news might have a detrimental effect on their product [16].

This general tendency among advertisers to avoid negative programs came from psychology literature, where researchers found that shifts of emotional state can be achieved easily through reading short passages of prose [6], seeing pictures of people [63], personal belongings [37], or films [29]. Researchers in advertising applied this to advertising and found that for both print and TV ads, the viewers' mood at the time of exposure to an advertisement influenced the processing of the advertisement [25]. In addition, researchers observed that TV program induced sentiment also could affect ad recall and cognitive responses toward the advertisement [46]. This research direction motivated us to ask the question: will the emotional sentiment of people's preferred video ads differ depending on the emotional state stimulated by companion content? We designed our second study to answer this question.

Table 2: The table lists the sentiments and example advertised products of the four sentiments that we chose for our study. These sentiments explain the mood of the ads for the product

	Synonyms	Example Advertised Products
Active	energetic, adventurous	Sports shoes
Alert	attentive, curious	Life insurance
Amusing	humored, laughing	Soda
Calm	soothed, peaceful	Cruises

3 STUDY 1: IMPACT OF PERSONALITY TRAITS ON SENTIMENTS OF PEOPLE'S PREFERRED ADS

3.1 Goal

The goal of our first study is to understand whether people's personality traits can predict the emotional tone or sentiment of the video ads that they prefer the most.

3.2 Material

To design this study, we first consulted the video ad dataset published by Hussain et al. [35]. The dataset had 3477 standalone video ads that were collected from both internet providers and YouTube. The authors considered only those ads which had at least 200,000 views and more "likes" than "dislikes". They also removed videos that were of low-resolution, very old, spoofs, or simply not ads. Hussain et al. [35] recruited Mechanical Turkers to collect sentiment labels for these videos. In the end, they categorized these videos in 30 different sentiments. Of these 30 sentiments, only nine sentiments appeared for at least 100 videos. For our analysis, we used ads from those nine most common sentiments that consisted of 2913 video ads.

We ran a pilot study with ads from these nine sentiments and found that some of those sentiments were similar to each other. For example, when we asked MTurkers to distinguish ads as being amazed, amused, or cheerful separately, it was challenging for them to distinguish among these ad sentiments. So, we combined them into the following four sentiments, which were clearly distinguishable from each other: 1) active, 2) alert, 3) amusing, and 4) calm. Table 2 shows the synonymous sentiments and example advertised products for these four selected sentiments.

3.3 Study Procedure

We created an online platform to conduct the study. First, our participants completed a 10-item measure for the Big-Five dimensions of the personality traits [28]. This 10-item measure (TIPI) was developed for situations where the full survey may not be a practical option. It has been shown that the TIPI reaches adequate convergence with the primary Big-Five personality trait measures in self-reported ratings [10]. Since we wanted to design a study no more than 30 minutes long, in our study, we used TIPI to measure personality.

Next, we asked each participant to watch four video ads sequentially. Each ad was randomly picked from the video ad pool, specifically for one of the four selected sentiments. So, each participant watched one active ad, one alert ad, one amusing ad, and one calm ad. We randomized the sequence in which our participants watched these ads. After watching each ad, our participants completed a short survey about that specific ad. This survey allowed us to understand the opinion of the participants about that ad. In the end, each participant chose one specific ad (among their four assigned ads) that they liked the most. We used this choice to run classification algorithms. Finally, participants completed a demographic survey.

3.4 Measures in the survey

To measure the opinion of the participants about the ads, we designed a survey. Our survey design was motivated by a measurement called "ace score" which was proposed by ACE Metrix [1], a company that measures the performance of advertisements and provides performance metrics to the concerned company. The seven factors that Ace Metrix proposed to measure the ad performance are as follows: watchability, information, change, desire, relevance, likeability, and attention. Some of these factors were not suitable for our survey. For example, we did not consider the "change" factor because this factor measures if the product (shown in the ad) is moving in a new direction over time. To answer this question about change, the participants had to have prior knowledge about the product. However, in our case, participants might not necessarily have that prior knowledge. Keeping the seven factors proposed by Ace Metrix in mind, we consulted the large body of literature on effective advertising [55, 56, 65, 69] and selected factors that were widely used to measure individual responses of potential consumers on ads and were also similar to the factors proposed by Ace Metrix.

The following are the ten factors that we ultimately assessed in our survey: repeatability, information, ad-attitude, uncommonness, creativity, relevance, ad-experience, a/v quality, involvement, and purchase intent. In total, we used 30 questions to measure these ten factors. Table 3 lists one sample question from each of these ten factors.

Table 3: Representative survey questions for measurement factors

Survey Measures	Sample Question
Repeatability	If you need to watch this ad many times in future, how will you feel? Not at all excited ——- Extremely excited
Information	The information received from the ad about the product was useful. Not at all useful ——- Extremely useful
Ad-Attitude	Rate your attitude towards the ad. Bad ——- Good
Relevance	The ad presented the product/service in a way so that it seems appropriate for you. Not at all appropriate ——- Extremely appropriate
Ad-Experience	Are you feeling attentive after watching the ad? Not at all ——- Extremely
Creativity	The ad was very creative in that the product/service was presented in a fresh new way. Strongly disagree ——- Strongly agree
A/V Quality	The visual elements of the ad (e.g., images, colors, lighting, etc.) were of high quality. Strongly disagree ——- Strongly agree
Uncommonness	The ad was uncommon. Strongly disagree ——- Strongly agree
Involvement	Please judge the ad against a series of descriptive scales presented below from your own perspective: Mundane ——- Fascinating
Purchase Intent	How likely will you like to buy this product in future? Not at all likely ——- Extremely likely

3.5 Participants

We recruited participants from Amazon Mechanical Turk (MTurk) for a user study. Prior work showed that MTurk workers can perform complex skill-intensive work as well as subjective rating tasks [8, 44, 54]. Moreover, researchers found that MTurk is a valid recruitment tool for research studies as MTurkers roughly represent the US population [36, 43]. In total, we recruited 600 MTurkers for our study. We included ratings collected from N = 589 participants in our analysis after removing participants who missed the attention check question. Participants' average age was 38.71 (SD=8.36), and 48% were females. All participants were at least high school graduates, and 40% of participants held a bachelor's or graduate degree. On average, each participant took 35 minutes to complete the study and received $2.5 for their participation.

3.6 Results

In our analysis, we considered the personality traits each as independent variables. So, we had five independent variables: extraversion, agreeableness, neuroticism, openness, and conscientiousness. To determine dependent variables, we conducted factor analyses on all ten factors measured from the surveys. We identified four factors from factor analyses that we used as dependent variables in regression analyses. We controlled our regression analysis for the product type (e.g. sports equipment, accessories, insurance etc.) and demographic data (e.g. gender) so that we could observe the effect of the personality traits on the sentiment of preferred video ads independently. Prior work showed that people's personality traits may depend on gender [17]. We used Nagelkerke's R^2 [51] to measure the quality of our model at each step. Finally, we used SVM to classify users preferred ads' sentiment based on their personality traits.

3.6.1 Factor Analysis. To analyze the variability of the measured factors and to reduce dimensions, we performed factor analysis on all ten dependent variables. This analysis allowed us to identify if multiple dependent variables had similar patterns of responses because of their association with a single latent variable. To maintain orthogonality among the reduced factors, we used varimax rotation for principal component extraction. This technique prioritizes a small number of factors with large loadings to draw out the most significant relationships and reduce noise. We also set a cutoff value of 1 for the eigenvalue of each factor. We identified four main factors for ads across all four sentiments. We found that ad attitude, uncommonness, and creativity factors had high loadings ($>$1.58) for a single factor. Therefore, we combined these three factors to create a new factor called "overall attitude". We also found that ad-experience, a/v quality, and involvement factors had high loadings ($>$1.23) for another single factor. So, we combined them to create a single factor of the ad's "overall experience". Finally, we found that information, relevance, and purchase intent factors had high loadings ($>$1.04) for a single factor. Therefore, we combined these three factors to create a new factor called the ad's "overall usefulness". For combining multiple factors into a single factor, we took an average of all the factors and used the average value as the new factor. For example, for combining ad attitude, uncommonness, and creativity factors into a single factor, we averaged their values for each participant and then used the average value as the overall attitude for that participant. Similar approaches were taken for overall experience and

Table 4: β coefficients of the linear regression analysis performed on the participants' opinion about active video ads. Asterisk($*$) denotes statistical significance (p $<$ .05). Participants with high extraversion and openness preferred the active ads the most.

	Repeatability	Overall Usefulness	Overall Attitude	Overall Experience
Extraversion	1.34(<0.01)*	0.96(0.01)*	1.02(0.01)*	0.87(0.02)*
Agreeableness	0.26(0.11)	0.19(0.16)	0.22(0.12)	0.73(0.04)*
Neuroticism	0.54(0.10)	0.34(0.19)	0.45(0.18)	0.43(0.31)
Openness	0.76(0.04)*	0.53(0.23)	1.48(<0.01)*	1.17(<0.01)*
Conscientiousness	0.25(0.14)	0.66(0.22)	0.51(0.29)	0.65(0.04)*
Goodness of Fit (R^2)	0.35	0.34	0.29	0.41

Table 5: β coefficients of the linear regression analysis performed on the participants' opinion on alert video ads. Asterisk($*$) denotes statistical significance (p $<$ .05). Participants with high agreeableness preferred the alert ads the most.

	Repeatability	Overall Usefulness	Overall Attitude	Overall Experience
Extraversion	0.41(0.31)	0.38(0.40)	0.43(0.19)	0.43(0.22)
Agreeableness	0.63(0.07)	1.31(<0.01)*	0.98(0.01)*	1.22(<0.01)*
Neuroticism	0.34(0.16)	0.19(0.32)	0.71(0.26)	0.19(0.25)
Openness	0.62(0.22)	0.34(0.29)	0.19(0.21)	0.23(0.21)
Conscientiousness	0.34(0.17)	0.36(0.18)	0.42(0.25)	0.79(0.03)*
Goodness of Fit (R^2)	0.36	0.32	0.37	0.35

overall usefulness. The remaining factor (repeatability) could not be combined in any of these combined factors. So, we considered the following four factors for multinomial regression analysis: overall usefulness, overall attitude, overall experience, and purchase intent. Next, we explain the results of regression analysis separately for the four emotional sentiments.

3.6.2 Results of multiple regression analysis. Since we used video ads of four different sentiments, we performed multiple regression analyses for each ad sentiment and each dependent factor separately. For purposes of clarity, we organized the findings of regression analyses based on each ad sentiment.

Active Ads. Table 4 shows the results of multiple regression analyses measured for the active video ads. Our regression analysis shows that participants with high extraversion and high openness preferred the active ads the most. All dependent variables were statistically significant for the participants with high extraversion, whereas, for participants with high openness, all predictors except overall usefulness were statistically significant. For participants high with agreeableness and conscientiousness, although overall experience was statistically significant, no other predictor variable was significant for the active ads. For participants with high extraversion and high openness, all statistically significant predictors had positive coefficients.

Alert Ads. Table 5 shows the results of the regression analyses for the alert video ads. We found that participants with high agreeableness preferred alert ads. All predictor variables except repeatability were statistically significant for the participants with high agreeableness, and they had positive coefficients. Among all the predictor variables for the participants with high agreeableness, overall usefulness had the largest positive coefficient.

Amusing Ads. Table 6 shows the results of the regression analyses for the amusing ads. Here, participants with high extraversion preferred the amusing ads the most. All predictor variables except overall usefulness were statistically significant for the participants with high extraversion. For participants with high extraversion, all statistically significant predictors had positive coefficients. Among all the predictor variables, repeatability had the largest positive coefficient followed by the overall attitude.

Calm Ads. Finally, Table 7 shows the results of regression analysis for the calm ads. Here, we observed that participants with high neuroticism preferred the calm ads the most, and all predictor variables were statistically significant for them. For participants with high neuroticism, all statistically significant predictors had positive coefficients. Among all the predictor variables, the overall usefulness had the largest positive coefficient followed by repeatability.

3.6.3 Results of Prediction algorithms. Prior work showed that SVM and C4.5 classifiers can satisfactorily predict users' behavior based on personality traits [14, 45, 58]. In our work, we used SVM classifier with RBF kernel and C4.5 to predict the sentiment of participants' preferred ad (recorded at the end of the survey). C4.5 uses decision tree for classification [61]. Before using the ratings of the personality traits for each participant in classifiers, we calculated pairwise correlation coefficients of the five personality traits. Table 8 shows the Pearson correlation coefficients across all possible pairs. Although we found significant correlations between extraversion and openness traits (as high as 0.53), all coefficients were below the selection criteria used in the test for multi-collinearity in previous work [9]. We used leave-one-out 10-fold cross-validation to obtain the average performance. For multi-class classification, we used 1-against-the rest method. The average performance across all

Table 6: β coefficients of the linear regression analysis performed on the participants' opinion about amusing video ads. Asterisk($*$) denotes statistical significance (p $<$ .05). Participants with high extraversion preferred the amusing ads the most.

	Repeatability	Overall Usefulness	Overall Attitude	Overall Experience
Extraversion	1.54(<0.01)*	0.51(0.09)	1.09(0.01)*	0.92(0.02)*
Agreeableness	0.78(0.04)*	0.28(0.21)	0.47(0.26)	0.51(0.14)
Neuroticism	0.41(0.20)	0.34(0.19)	0.27(0.13)	0.25(0.31)
Openness	0.82(0.16)	0.48(0.22)	0.57(0.19)	0.83(0.03)*
Conscientiousness	0.34(0.11)	0.52(0.15)	0.61(0.23)	0.59(0.09)
Goodness of Fit (R^2)	0.34	0.37	0.31	0.33

Table 7: β coefficients of the linear regression analysis performed on the participants' opinion about calm video ads. Asterisk($*$) denotes statistical significance (p $<$ .05). Participants with high neuroticism preferred the calm ads the most.

	Repeatability	Overall Usefulness	Overall Attitude	Overall Experience
Extraversion	0.22(0.17)	0.34(0.27)	0.62(0.22)	0.41(0.23)
Agreeableness	0.43(0.31)	0.27(0.12)	0.56(0.23)	0.53(0.10)
Neuroticism	1.13(<0.01)*	1.28(<0.01)*	1.09(0.01)*	0.89(0.02)*
Openness	0.57(0.08)	0.42(0.15)	0.28(0.16)	0.63(0.14)
Conscientiousness	0.41(0.27)	0.47(0.31)	1.29(<0.01)*	0.38(0.13)
Goodness of Fit (R^2)	0.32	0.29	0.35	0.37

Table 8: Pearson correlation coefficients across personality traits (independent variables). Here, O: Openness, C: Conscientiousness, E: Extraversion, A: Ageeableness, and N: Neuroticism. We observed highest correlation between extravesion and openness

	O	C	E	A	N
O		0.22	0.53	0.39	0.10
C			-0.19	0.21	-0.04
E				-0.12	-0.34
A					0.25
N					

Table 9: Precision, Recall, and Accuracy measures of SVM and C4.5 classifiers. SVM performed better than C4.5 for our dataset.

	Precision	Recall	Accuracy
SVM	0.86	0.93	0.96
C4.5	0.78	0.85	0.93

folds is listed in table 9. We reported precision, recall, and accuracy measures. The results show that sentiments of users' preferred ads can be predicted using their personality traits. Here, SVM performed better than C4.5. Further investigation showed that extraversion and openness traits predicted sentiments of users' preferred ads better than all other traits.

3.6.4 Summary of Study 1. Our regression analysis and classification algorithms show that people's personality traits can predict the sentiment of their preferred video ads. Prior work in this domain showed that people with high openness and low neuroticism are favorable to online ads. Our work took a step further and showed that the sentiment of preferred video ads can be predicted based on people's personality traits. The ad sentiments preferred by the participants were consistent with the characteristic features of their personality traits (as mentioned in Table 1). For example, participants with high extraversion and openness preferred active ads. Since most of the active ads featured situations where actors were trying new challenging activities and celebrating with friends, it matched the basic features of the extraversion and openness traits, and therefore, participants having those traits preferred to watch these ads. Similarly, we believe that participants with high neuroticism preferred to watch calm ads portrayed relaxing and soothing experiences because these ads pacified their emotional restlessness. One possible reason why participants high in agreeableness preferred alert ads is that alert ads often first introduced a threat scenario and then proposed a safe preventive solution. We believe that people high with agreeableness trusted the solution presented in these ads. Finally, amusing ads were often about fun and enjoyment with friends and family, which matches the essential features of the extraverted personality.

This finding can assist advertisers in designing their ads based on their target customers and target media. For example, for the same product, advertisers may choose to create one amusing ad and another calm ad and broadcast them selectively in different media that may have properties that attract different personality types. Audiences may become interested in these ads because of the better match of their sentiment preferences, which could make them aware of new products available in the market.

The finding of our first study is promising. However, in this study, we asked participants to watch only ads on their own without any companion content, which is not realistic. In real life, people encounter ads most often when they also access content such as when reading a news article or a social media update from a loved one. While our first study looked at the more long-term, trait-level factor of personality, personality provides a range for which more momentary state-level fluctuations in emotion occur. Our first experiment did not consider participants' natural preferences when the ad is presented within a context that causes a more immediate emotional response. We hypothesized that in addition to their personality traits, an audience's initial emotional state can affect the sentiment of their preferred video ads. So, we conducted our second study to analyze the effect of temporary, context-induced emotion along with more-stable, long-term personality traits.

4 STUDY 2: IMPACT OF COMPANION CONTENT ON SENTIMENTS OF PEOPLE'S PREFERRED ADS

4.1 Goal

The goal of our second study is to understand whether and how a temporary emotional state (such as that stimulated by companion content) can predict the sentiment of the video ads that people will prefer the most.

4.2 Material

To design this study, we used the same set of video ads that we used for our first study. Prior work showed various techniques to stimulate emotional sentiment among participants such as playing music [40], showing pictures [7, 20], showing movie segments [57, 62], and reading articles or stories [32, 64]. To induce the sentiment of companion content that the audience would encounter as media content, we used the story prompts by Harmon-Jones et al. [32]. Harmon-Jones designed these story prompts based on the emotional themes identified by past research. They found that these story prompts can assist people in reliving a specific incident from the past that then prompts one to experience a particular emotional state. Since all the emotions mentioned in this article were broadly classified as either a positive or negative emotion, we decided to use two positive, and two negative emotion stimulating story prompts in our study. We adopted the "relaxation" and "reward" story prompts to stimulate positive emotion, and the "anger" and "disgust" story prompts to stimulate negative emotion among our participants. Here is an example of a positive story prompt: *"Please remember a SPECIFIC time when something wonderful had just occurred. You received something you wanted very much for a long time, or you achieved an important goal, or you received a very prestigious award. Please think of a positive situation for some time, when something very good had happened to you, in which you experienced an extremely intense positive emotional response."*[Relaxation story prompt]

4.3 Study Procedure

We reused the online platform created for the first study with some modifications. After signing the consent form, our participants completed the same 10-item survey for the Big-Five dimensions of the personality traits as they did in study 1. Next, to simulate the emotion that can be induced by companion content, we asked half of our participants to read a positive (either relaxation or reward) story prompt and the other half to read a negative (either anger or disgust) story prompt. Next, we asked them to take some time (5 min) to relive that situation that they thought of and to re-experience the emotions they felt at that time as strongly as possible. We asked them to go on to the next screen when they had the experience in mind, and the emotions were strong.

We asked participants to complete a short emotional state survey where participants chose their emotional state on a scale of 1 to 10 where 1 means "Negative and Forceful" and 10 means "Quite Positive" [3]. Additionally, we asked them to rate on a scale of 1 to 7 (where 1 means "strongly disagree" and 7 means "strongly agree") about how 1) happy/joyful, 2) enjoyment/fun, 3) unhappy/sad, and 4) frustrated/angry they were feeling. Next, we randomly assigned a video ad to each participant to watch from our video ad pool. We divided our participants who read a positive story prompt into four sub-groups. Participants of the first sub-group watched an active video ad, the second sub-group watched an alert video ad, the third sub-group watched an amusing video ad, and the fourth sub-group watched a calm video ad. We did a similar distribution for the participants who read a negative story prompt. Unlike the first study, we did not ask each participant to watch more than one ad in this study because we hypothesized that the emotional state induced by the story prompt would be weak when participants would watch more than one ad. After watching their assigned ad, our participants completed the same survey that we used for study 1, which allowed us to understand their opinion about the ad. Finally, participants completed a demographic survey.

4.4 Participants

We recruited 800 participants from MTurk. In the end, we included ratings of N = 772 participants in our analysis after removing participants who missed the attention check question. Participants' average age was 33.93 (SD=12.66), and 44% were females. All participants were at least high school graduates, and 43% of participants held a bachelor's or graduate degree. On average, each participant took 22 minutes to complete the study and received $2.5 for their participation.

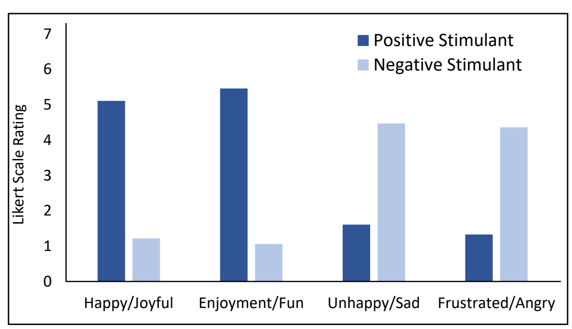

Figure 1: The average rating of the participants in the emotional state survey. Participants exposed to the positive story prompt stimulant felt significantly more positive emotions than negative emotions and vice-versa.

Table 10: R^2 value of the hierarchical multiple regression models on the participants' opinion about active, alert, amusing, and calm video ads. Asterisk($*$) denotes statistical significance (p $<$ .05). For alert and calm ads, the emotional state variable significantly improved the regression models.

		Repeatability	Overall Usefulness	Overall Attitude	Overall Experience
Active	Personality Traits	0.35	0.34	0.29	0.41
	Emotional State	0.38	0.36	0.33	0.42
	Δ R2	0.03	0.02	0.04	0.01
Alert	Personality Traits	0.36	0.32	0.37	0.35
	Emotional State	0.45	0.42	0.48	0.48
	Δ R2	0.09*	0.10*	0.11*	0.13*
Amusing	Personality Traits	0.34	0.37	0.31	0.33
	Emotional State	0.40	0.42	0.37	0.38
	Δ R2	0.06	0.05	0.06	0.05
Calm	Personality Traits	0.32	0.29	0.35	0.37
	Emotional State	0.41	0.33	0.46	0.49
	Δ R2	0.09*	0.04	0.11*	0.12*

4.5 Results

In our analysis, we considered all five personality traits as independent variables. Additionally, we considered participants' emotional state as an independent variable. Similar to study 1, we performed factor analysis to reduce the number of dependent variables. Based on the result of the factor analysis, we finalized the same four dependent variables (repeatability, overall usefulness, overall attitude, and overall experience) for further analysis as we did in the first study. Since the main motivation of this study is to understand the impact of temporary context-induced emotion along with longer-term personality traits, we performed hierarchical multiple regression analysis to process participants' opinions. We initialized our regression model with the product type and demographic data. We called this initialization process "step 0". In step 1, we added the personality trait variables, and in step 2, we added the emotional state variable in our model. We used Nagelkerke's R^2 [51] to measure the quality of our model at each step.

To verify the effect of our positive and negative stimulant, we analyzed responses on the emotional state survey. Figure 1 shows the ratings of two positive and two negative emotions. Since the two positive emotion ratings were significantly correlated (r = 0.82), we took an average of the two ratings for each participant. Similarly, we took an average of the two negative emotions for each participant since they were also highly correlated with each other (r = 0.76). We performed an independent sample t-test and found that participants exposed to the positive story prompt, felt significantly more positive emotions (M = 5.28, SD = 0.96) than negative emotions (M = 1.47, SD = 0.96), t(394) = 3.91, p $<$ 0.01. Similarly, participants exposed to negative stimulant expressed significantly more negative emotion (M = 4.42, SD = 0.91) than positive emotion (M = 1.14, SD = 0.89), t(374) = 3.43, p = 0.01. These results show that our story prompts successfully induced positive or negative emotions among our participants similar to what they would possibly feel by reading companion news articles, seeing a loved ones' posted photo memory, or watching an emotional video.

Next, we performed a hierarchical regression analysis on the ratings of the participants for their assigned video ads. Our purpose was to understand whether emotional stimulation has any effect on participants' ratings in addition to the personality traits. Table 10 shows the outcome of the regression analysis for video ads for all four sentiments. Due to space limitation, we did not report the beta coefficient of all the independent variables; rather, we show the R^2 value of the regression model both at step 1 and at step 2. We also reported if the ΔR^2 values (the difference of R^2 values at step 1 and step 2) were statistically significant or not. The effect of the personality traits was consistent with the findings of study 1. Given that the main focus of our second study was to observe the effect of the emotional state, we discuss mostly the effect of emotional state in this section. We found that for alert ads, ΔR^2 values were statistically significant for all dependent variables. This indicates that the emotional state variable significantly improved our model for alert ads. We observed a similar trend for the calm ads, although for calm ads, ΔR^2 value was not significant for overall usefulness. For active and amusing ads, the ΔR^2 values were not statistically significant, which indicates that the emotional state variable did not significantly improve our regression model for those types of ads.

These findings indicate that for some ads (alert and calm), the emotional state induced by the story prompts affected the sentiment of preferred video ads of the participants, although, for the other types of ads (active and amusing), the effect was not significant. To understand these findings better, we performed a more thorough regression analysis where we only analyzed the ratings of the participants who watched either an alert or a calm ad. Here, for the alert ads, we again initialized our model with the product type and demographic data, and in step 1, we included the personality trait variables. However, in step 2(a), we included the emotional state variable of only those participants who were exposed to a positive story prompt. Next, in step 2(b), we removed the emotional state variable added in step 2(a). Instead, we included the emotional state variable of those participants who were exposed to a negative story prompt. This model creation process allowed us to observe the effects of the positive and negative emotions separately for the alert ads. We performed the same process for the calm ads too.

We found that for participants who were exposed to a negative story prompt and later watched an alert ad, their emotional state variable significantly improved our regression model. On the other hand, when participants were exposed to a positive story prompt and later watched a calm ad, their emotional state variable also significantly improved our regression model. However, for the remaining two scenarios (exposed to a positive story prompt and watched an alert ad and exposed to a negative story prompt and watched a calm ad), the emotional state variable did not significantly improve the regression model.

4.6 Summary of results in study 2

These findings of study 2 show that the emotional state induced from certain types of companion content (negative stimulation for alert ads and positive stimulation for calm ads) can significantly affect the sentiment of people's preferred video ads. However, for active and amusing ads, the emotional state did not affect people's ad preferences. One explanation is that active and amusing ads were mostly fast-paced ads, which either showed active participation of the actors in some physical activities or showed fun activities while playing cheerful music in the background. These types of video ads might have weakened the effect of the emotional state since the induced state was subtle. On the other hand, negative stimulation for the alert ads and positive stimulation for the calm ads were contextually relevant. Moreover, in general, alert and calm ads were slow-paced. They were more informative, and generally, they used soothing background music to create a relaxing experience. These factors might have bolstered the effect of the subtle emotional state, which motivated our participants to get more involved with those ads. Overall, the emotional state explained a modest amount to additional variances of the model (about 10-13%), on top of product types, demographic data, and people's personality traits.

5 DISCUSSION

Researchers had previously found that personality traits can impact people's preference for ads in general [12]. To our knowledge, our paper is the first to show that people's personality traits can reliably predict the sentiments of their preferred video ads. Additionally, we observed the effect of context-induced emotional state on the video ads and found that for certain types of video ads, the emotional state can significantly affect people's ad preferences, even beyond their personality.

Our findings are consistent with the findings of Govers et al. [30] who found that congruence with a brand's personality can positively improve people's preference for a product. These findings can benefit advertisers to evaluate their advertising strategy for certain brands. Based on the target customers, advertisers can determine the sentiment that they want to highlight in their video ads. They can also highlight different sentiments for different versions of the same ad. Later, they can decide which version of the ad will be the most suitable for a particular media (such as television and social media) based on the expected audience's response to that specific media content. This approach can also create opportunities for the corresponding product owners to attract the attention of new customers for their existing products. We hope that such approaches benefit the audience as well by providing preferred content over annoying or irritating ad content.

Our findings from the second study suggest that placing video ads with randomly selected companion content may not be a smart approach from the perspective of a product owner. Instead, a product owner or their advertiser should consider the emotional state induced by the companion content, as well as the personality types that might be attracted to that content to maximize the effectiveness of their advertisements. This smart ad-placing approach, consistent with the concept of optimal advertising [52], can be a practical solution for medium and smaller brands who want to maximize the benefit of their video ads by paying for fewer ad placements in the media. Additionally, this approach may be beneficial for the content creators as well as the audience as the audience will enjoy the video ads more and because of that, they would might be less annoyed and may engage with the companion content more as well.

Our findings do not necessarily suggest that advertisers should continuously follow users' online activities to determine their personality traits for effective ad targeting. Nor do we claim that targeting video ads based on personality traits is the most effective way to maximize the goal of advertising. Instead, we believe that our findings will assist advertisers in designing their ads for a broader range of audiences and contexts while also making them more in line with individual preferences. Future work could identify features of companion content that would best allow prediction of both the sentiment created for the audience as well as what personalities might be attracted to that content. Thus, making the targeting more dependent on context than on the individual audience member.

We want to stress that we believe such ads should only be placed on the media with proper consent from the audience. People *may* provide their consent not only to access free content but also to watch more preferable ads instead of watching randomly picked ads. However, this requires explicit, accountable control settings.

It is important to note that preferred content is not equivalent to beneficial content. A person may enjoy a fast food advertisement, but targeting and biased, discriminatory targeting have long term consequences that affect society. Our findings will provide a better understanding of people's ad preferences. These findings, however, are not without ethical consequences with respect to privacy, moral, and societal obligation. More research is needed to better understand practices so that we can better align not only people's preferences but also their societal and privacy expectations with those of advertisers. Moreover, more work is necessary to inform users of ad practices so that they may have a voice in the advertiser-audience dynamic.

6 LIMITATIONS

In our paper, we considered only four sentiments while choosing our video ads. In the future, we need to analyze a wider range of sentiments to increase the generalizability of our results. Additionally, we conducted a quantitative study to understand the impact of personality traits and emotional state induced by companion content on sentiment of people's preferred ads. A qualitative study can be conducted on this topic to reveal possible causal relationship among these components. Finally, to replicate the emotional state stimulated by companion content, we used story prompts. A more thorough study with real companion content such as news articles or social media posts would help us understand the full impact of those contents on people's emotional state.

7 CONCLUSION

Video ads play a key role in making products or brands known to the audience, but advertisers often struggle to attract people's attention and liking to their ads. This paper made two important contributions in this domain. In the first study, we identified how people's personality traits can predict the emotional sentiment of their preferred video ads. In the second study, we revealed the effect of a temporary emotional state on people's ad preferences. This paper contributes to the IUI community by furthering our understanding of utilizing personality traits and emotional states in predicting audiences' ad preferences. We hope our findings inspire a healthy and transparent relationship between advertisers and their audience in the future.

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