Investigating the Role of Context and Personality in Mobile Advertising

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ABSTRACT

More than three billion smartphones carried by their users at virtually all times, represent an unprecedented platform for in-situ advertisement delivery. While recent efforts in data analysis and machine learning led to significant advances in the way relevant content is selected to be shown to a user, thorough investigation on how the content should be displayed to a mobile user is yet to be conducted. In this work we present our preliminary research on the role of the context in which an advertisement is consumed and the personality of a user consuming it on the perception of the ad content. We conduct a 7-week study with 14 mobile users who were exposed to both video and picture ads. Through mobile sensing and experience sampling we capture the information on the context in which the ad was seen, the user's attitude towards the ad, as well as the user's personality traits. Statistical analysis based on mixed-effect modelling demonstrates that personality traits play an important role in ad perception, as does the ad type, with picture ads being preferred to video ads, while the effect of the context on ad perception appears to be negligible.

CCS CONCEPTS

• **Human-centered computing → Interaction techniques**; **Ubiquitous and mobile devices**; Empirical studies in ubiquitous and mobile computing.

KEYWORDS

mobile advertising, multilevel models, ubiquitous computing

1 INTRODUCTION AND BACKGROUND

Tremendous amounts of digital traces, just-in-time sensor information, and the advances in data processing have resulted in major shifts in how the advertising is performed. Machine learning and recommender systems are at the core of modern advertising solutions [9]. The selection of the ad to be show to the user benefits from the history of purchases, information on the similarity among users, but also on the information about a user's personality [6].

Moving to the mobile domain, contextual information, such as location may impact the relevance of an ad [2]. The context, that can be sensed by a smartphone, such as a user's location, his physical activity, time of day, and other factors, can also be used to determine the suitability of a moment for information delivery [7].

While the previous work focuses on the content or the timing of the ad delivery, the type of the ad, to the best of our knowledge, has not been examined in the mobile domain. Nevertheless, the type of the ad, whether it is a picture, a short or a long video, or perhaps an interactive content (e.g. a short game) is an important parameter that influences the overall design of an ad, the platforms at which the ad can be shown, advertisement budget, etc. In this paper we focus on the perception of an ad type in mobile computing and pose the following research question: *Can the contextual information collected by the mobile phone sensors and the information on a user's personality predict a user's perception of different types of mobile ads?*

In the following sections we answer the above question through a real-world study of mobile advertisement usage and a thorough statistical analysis of the collected ad interaction, context, and personality data.

2 METHODOLOGY

To obtain ecologically valid data on mobile ad perception in different contexts we developed a data collection mobile application that serves ads, captures a user's attitudes towards the displayed ads, and collects sensor data pertaining to the context of use. In the rest of the section we present the details of our app.

Mobile Application

We implemented a full-fledged mobile app that caters to the need of our target users – students at our University. The application was built for the Android platform and serves as a utility tool allowing its users to: obtain information on nearby restaurants providing subsidised student meals, get real-time public transport timetables, record or share important student notes, retrieve latest student related news feeds, save and access their most needed school gadgets, and organise their class schedules (Figure 1 left).

Mobile ads. Mobile ads come in different flavours ranging from simple picture-based ads, over video ads, to more interactive game-like ads. We opted to investigate the two most

Figure 1: Data collection app: one of the functionalities (left), advertisement (center) and an ESM questionnaire (right).

frequent types of ads in our study – pictures and videos. We further divide the video ads into two groups – short videos, with the length of 30 seconds or less, and long videos with the length between 30 and 80 seconds. From each of the three groups – pictures, short videos, and long videos – we gathered 31 different publicly available ads and pre-loaded them on our server. After five actions that a user makes within our app, a request is made to our back-end system which responds with a random ad of a randomly chosen category. Simultaneously, we activate mobile phone's sensors and capture the user's context, including the physical activity (through Android's Google Activity Recognition functionality), location (clustered as *work*, *home*, or *other*, according to the method described in [7]), screen brightness, battery level, time of day, and the Internet connectivity type.

Experience sampling method (ESM) questionnaires. ESM is commonly used to gather the participants own thoughts, emotions, behaviour, etc [3]. In our case it provided us with feedback regarding the participants assessment of overall ad suitability. With the included questionnaire we also wanted to measure the interaction level between the user and the displayed ad. Thus, the questionnaire consisted of following questions: what was shown on the ad, which brand/trademark was advertised, and was the ad shown in an appropriate form. The first two questions were used to assess whether the user was engaged with the ad. The last question focused on the appropriateness of the displayed ad. The answers are recorded with five-level Likert scales. Figure 1 represents the data collecting workflow, where a user made an action, which led to the ad being displayed, followed by the ESM questionnaire.

Personality test. Previous research demonstrates that personality traits have a moderate effect on a user's attitude towards advertisement [1]. Therefore, we included the BFI-10 personality test [8] as a part of our app. The test includes ten questions about a user's traits answered on a seven-point Likert scale. The processed BFI-10 data, assessing a user's personality along the five dimensions (extraversion, agreeableness, openness, conscientiousness, and neuroticism), was further compared to the statistics calculated on a larger population set in order to extract the percentiles to which the participants personality trait scores belong [8].

Data collection campaign

Our data collection campaign lasted for seven weeks in spring 2020 and included 14 participants who in total viewed 994 ads, out of which 501 they labeled, i.e. an ESM questionnaire was completed immediately after the ad was viewed. The distribution of labeled and unlabeled ad types is roughly even. The viewing was reasonably evenly distributed among users, with the least active participant contributing 2.4% and the most active participant contribution 12.6% of the data. In our study we included 12 picture ads, 9 short video ads, and 10 long video ads. The ads were randomly shown both within and among users, i.e. each two users saw different ads where a participant shown a picture ad from a specific brand need not have seen a video ad from the same trademark. The majority of viewed ads, that are labeled, were pictures (40.5%), followed by short videos (34.7%). The least amount of user feedback was from long videos (24.8%). The average score (questionnaire answers ranging from "Strongly disagree" to "Strongly agree" were transformed to the integer

[-2, 2] scale) over all ads was 0.377, yet it differs across the ad types. Labeled pictures had an average score of 0.695, short videos 0.253, and long videos 0.032.

3 MOBILE AD PERCEPTION MODELLING

Our data collection study elaborated in Section 2 has resulted in a heterogeneous dataset with an uneven number of datapoints across users, across contextual characteristics, and ad types. The natural organisation of our data into groups makes multilevel modelling-based analysis particularly appropriate. Such models generalise the linear regression in a manner that allows that the effect of a group (e.g. a particular user, a personality type, etc.) is disentangled from the effect of predictors, such as contextual variables [4] [5].

With hierarchical modeling we gradually increase the model complexity by including different parameters as a part of fixed or random effects. At each step we need to compare our new model to the previous one. This is done by preforming a chi-squared test checking if the residual sum of squares of the new model is statistically significantly smaller than that of the old model. To further verify which model is better we calculated the AIC (Akaike information criterion) and BIC (Bayesian Information Criterion) metrics, where smaller values indicate a better model, since the relative amount of information lost is lower.

In this section we present the results of multilevel modelling with two models constructed on the labeled data in order to investigate the impact of different parameters on the ad perception – a model where the *user ID* is the grouping variable and a model where the user's *personality* is the grouping variable. We then use both labeled and unlabeled data in a semi-supervised learning fashion to construct our final predictive model rooted in users' personalities.

User ID-based model

The basic user model includes merely the participants' IDs as the grouping variable. From there on we gradually increase the model complexity by separately adding context-based parameters. We experiment with the inclusion of the physical activity, location, screen brightness, battery level, time of day, and the internet connectivity type information in our model, and find that none of the contextual variables have a statistically significant influence on whether a user marks an ad as appropriate or not. In addition, the comparison of the basic model with the context-based ones reveals that the AIC and BIC metrics increase, and the p-value of the chi-squared model comparison remains above the 0.05 threshold, again indicating the superiority of the basic model.

Since the context is shown to be irrelevant, we focus on the content and the type-based models. With the inclusion of ad type, as a part of fixed effects, we were able to build a model that preforms better then the basic one. We suspect that different users score different ad types in different manners, thus we included the type parameter as a random slope. Metrics AIC, BIC show a significant decrease, indicating that the new model preforms better than the previous one. The analysis of the model reveals that picture ads receive a predominantly positive score, short videos neutral-negative, and long videos very negative score. Slope coefficients for ad type were also found to be varying within users. We further experiment with content-based models, where the each particular ad is encoded as its own content category[1]. The AIC, BIC, and chi-square-based comparison indicate that the content has a statistically significant impact on ad scoring. With both content and ad type being relevant we further investigate whether it is possible to combine both models and also include the ad viewing duration as a parameter. Indeed, our best preforming model includes *the duration of ad watching*, and cross-level *interaction of ad content and ad type* as fixed effects, and *ad type* as the random effect. The conditional R^2 metric of such a model is 0.455 whilst the marginal R^2 is 0.204 indicating a reasonably good fit.

Personality-based model

The above user ID-based model demonstrates the impact of individual traits on the ad perception. Nevertheless, the model is not suitable for real-world use, as it requires that an individual's data is available *before* predictions can be made. Therefore, we now design a model that, instead of data from a particular user, is based on the information about personality traits of a user. Such information can be obtained quickly through a personality test.

The basic personality-based model only includes a grouping variable based on personality traits without any fixed effects or random slopes. As before, we find that the inclusion of context parameters does not improve the basic model so we focus on the ad content and ad type as the next modeling level. Gradually increasing the complexity of our model we come to similar conclusions as in the previous section. The fixed effects include a cross-level interaction of ad content and ad type, where the random effects include ad type only. The final personality-based model demonstrates that ad types are marked differently within different personality groups. One particular group consisting of extrovert, non-conflicting, non-conscious, and emotionally stable users is found to stand out. In the mentioned group pictures had an average score of -0.4, short videos 0.636 and long videos -0.75. To see if the scores were indeed significantly different, we preform a Welch's t-test between this outlying and all other personality groups (Table 1). We find that the difference in

[1]While a more abstract grouping is possible (e.g. different car-related ads grouped in "cars" category), due to a small number of ads we opted for individual ad-categories.

short video scoring between the compared groups is not statistically significant, whilst the scores of pictures are.

Metrics	Pictures	Short videos	Long videos
t-test	-4.087	1.026	-1.545
p-value	0.001	0.326	0.162
95% conf. interval	[-1.771, -0.565]	[-0.467, 1.286]	[-2.089, 0.416]
Outlying group avg.	-0.4	0.636	-0.75
Other groups avg.	0.768	0.227	0.086

Table 1: Welch's t-test between the outlying personality group (extrovert, non-conflicting, non-conscious, and emotionally stable) and other personality groups.

Even though we built a personality-based model with the intent to make it more general, we found that not all personality combinations are included, as our sample size is not large enough. With 14 participants, out of 16 different possible personality groups (openness omitted) only 7 are covered. The final model's R^2 metric conditional value is 0.377 and the marginal is 0.198.

Predictive personality-based model

The user ID-based model demonstrates that *who* is watching the ad is more important than *in what situation* is someone watching the ad. Predictions of an attitude towards an ad could be used to decide whether to show an ad of a certain type, or whether to show an ad at all. Yet, personalised user-based models would require labeled data for each user, making their construction impractical. The analysis of the personality-based multilevel models demonstrates that general personality traits, obtainable through a simple 10-item questionnaire, can be used to build an informative model. Here we examine the predictive potential of a fully generaliseable model based on personality traits information.

With semi-supervised learning, we first label the unlabeled data – using the previously constructed user ID-based model, we predict the labels for the 493 unlabeled points. We then proceed with constructing a new personality-based model. Repeating the gradual increase of complexity procedure we find that the following context variables significantly impact the fit: screen brightness, battery level, and Internet connection type. Nevertheless, the variables do not feature highly in the final model, as ad content and ad type prove to be much more impactfull on the final ad scoring. Our final generalised personality-based model constructed on all gathered data includes a cross-level interaction of ad content and ad type as fixed effects and ad type as a random effect.

To assess the potential of the model to correctly predict the score a previously unseen user will give to an ad in a certain situation, we perform a leave-one-person out evaluation and in each step calculate the (root) mean square error (R)MSE and mean absolute error (MAE) of our model and the baseline model that predicts the mean score across the dataset. Average RMSE, MSE, and MAE for the personality-based model are 0.967, 1.014, and 0.785, whereas the baseline results in 1.117, 1.347, and 0.865, respectively, indicating that the personality-based predictive model fits the data better than the majority classifier. The R^2 metric's conditional value of the model is 0.488 and the marginal is 0.308.

4 DISCUSSION AND CONCLUSION

In this paper we examined of the role of context and a user's personality on ad perception. While our initial assumption was that users would prefer either picture or video ads depending on the context of viewing, we discovered that picture ads are almost universally better accepted. This surprising finding might stem from our data collection limitations – conducted during the COVID-19 pandemics, the data fails to capture the full range of locations and activities we would expect to see during regular times. A prominent role of a user's personality in the perception of an ad is another interesting finding. We discover that certain personalities actually prefer short videos over picture ads. Our general predictive model takes personalities into account and is able to predict the attitude that a previously unobserved user will have towards an ad better than the baseline model. Nevertheless, the initial analysis also demonstrates that the content of the ad, a property that was outside of the scope of our study, may significantly impact the perception and should be further examined.

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