Understanding and Modeling User-Perceived Brand Personality from Mobile Application UIs

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ABSTRACT

Designers strive to make their mobile apps stand out in a competitive market by creating a distinctive brand personality. However, it is unclear whether users can form a consistent impression of brand personality by looking at a few user interface (UI) screenshots in the app store, and if this process can be modeled computationally. To bridge this gap, we first collect crowd assessment on brand personalities depicted by the UIs of 318 applications, and statistically confirm that users can reach substantial agreement. To further model how users process mobile UI visually, we compute UI descriptors including Color, Organization, and Texture at both element and page levels. We feed these descriptors to a computational model, achieving a high accuracy of predicting perceived brand personality (MSE = 0.035 and R^2 = 0.78). This work could benefit designers by highlighting contributing visual factors to brand personality creation and providing quick, low-cost design feedback.

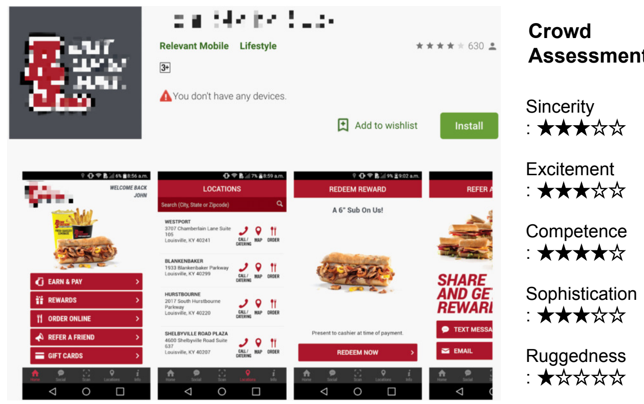

Figure 1: Each application on Google Play has several screenshots of its UI displayed in the app store. We invite crowd workers to rate the screenshots with respect to the perceived brand personalities in 5-point Likert scale from strongly disagree to strongly agree (0 being "strongly disagree").

CCS CONCEPTS

• **Human-centered computing** → **Graphical user interfaces**.

KEYWORDS

Mobile user interfaces; brand personality; computational design assessment

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1 INTRODUCTION

The user interface (UI) of a mobile application defines its look and feel, giving end users an early impression of the app's detailed design [51]. Designers often tailor the graphic representation of app UIs, (*e.g.,* color, layout, font, transition effect, *etc.*), to the target audience and context [1]. This is not only for engaging users by the appeal [49], but also for building competitive advantage in a crowded app market through the conveyance of a consistent brand personality [2, 15]. The development of brand personality, defined as "a set of human characteristics associated to a brand", contributes to users' perception and preference toward a product [22]. When expressed properly, brand personality, *e.g.,* high sincerity and competence for business apps [15], can positively affect user loyalty on, satisfaction with, and emotional connection to a mobile service [17, 27, 51].

As the brand personality of a mobile app is communicated indirectly through its look and feel, a gap may exist between designers' intention and users' perception [21, 53]. However, few empirical studies have investigated the extent to which users can form a consistent impression of brand personality (denoted as perceived personality in the rest of the paper) by looking at a few mobile UI screenshots in the app stores. Moreover, it is unclear which graphical features of the UIs contribute to such perception. Although prior work confirms that the graphical design of a website can adequately portray the traits of the website's associated brand [13], such findings may not be readily applied to mobile apps due to the unique nature of mobile interface, *e.g.,* smaller screen size, less content with higher simplicity, and more standardized design guidelines [38].

Hence, designers need to frequently elicit feedback from target users and/or domain experts during the iterative app design process to ensure the attractiveness, distinctiveness, and self-expressiveness of the designated brand personality. This approach, although deemed effective [20], may not be applicable for small companies and individual developers with limited budget and resources. Therefore, the demand for computational evaluation of designs has increased, because the results could provide rapid, low-cost, and relatively reliable design feedback, especially at the early design stages [38]. Although computational models of UI aesthetics [38], visual diversity [46], and interestingness [23] are widely available, they cannot be directly used to assess the perceived personality of mobile apps.

To bridge the gap, we explore the possibility of deriving a computational model of how general users perceive brand personality from mobile app UIs. We first interview professional designers to understand why and how they depict brand personality in mobile app UIs. Based on their insights, we propose a data-driven framework for modeling how well users can relate to various brand personality traits simply by looking at the screenshots of an app. Following the framework, we collect a large set of crowd assessments on the perceived personalities of 318 apps. The statistical results confirm that users can form consistent perceptions of brand personality traits; extroverts tend to rate UIs with higher personality scores than introverts do.

To model how users process the look and feel of an app, we translate three aspects of mobile UIs (*i.e., Color*, *Texture*, and *Organization*) into computable visual descriptors using metrics from the existing literature that are effective in measuring users' visual experience. Then, we feed the descriptors into a machine-learning (ML) model to predict the perceived personality of mobile app UIs. Our model achieves high prediction accuracy (mean squared error (MSE) = 0.035, R^2 = 0.78), whereas random guess has a MSE of 0.135. It suggests user perceived personality of mobile apps can be predicted with reasonable and reliable performance. We further leverage the model to identify visual factors that have a considerable effect on user perception of brand personality. We find that colorfulness, color-induced pleasure, number of text areas, and symmetry stand out among all features. Overall, the human rating dataset, predictive model, and findings presented in this paper could benefit the future designs of personality-enriched mobile UIs.

2 RELATED WORK

Personality of Design

Human personality that characterizes a particular person has long been studied to analyze human behavior towards certain environments [43]. Researchers extend this concept to model brand personality, defined as "the set of human characteristics associated with a brand", which captures user perception and preference toward a brand [2, 26]. To measure brand personality, Aaker *et al.* develop a scale for measuring the five dimensions of brand personality, *i.e.,* Sincerity, Excitement, Competence, Sophistication, and Ruggedness, derived from the 'Big Five' human personality structure. Such measurements have been shown to be a reliable and valid assessment of brand personality [4]. Chen *et al.* further investigate how consumers perceive website personality with regard to brand and human-oriented features of websites [13]. The finding suggests that brand personality of websites can be consistently perceived and recognized. Likewise, Poddar *et al.* reveal that the websites reflecting a lively, friendly, and welcoming atmosphere inform enthusiastic personality [45]. Similar to websites, mobile apps are also brand carriers and present features that are associated with human preferences [7]. These findings inspire this work to investigate whether mobile app personality can be consistently perceived, which has not been studied before.

Embodying Personality into Design

Past research suggests that embracing personality into a design is critical as it can affects users' perception and behavior toward the product [40, 41]. The relevant studies fall into two streams. One highlights the effects produced by the brand personality of a design. In particular, the embodiment of brand personality has been demonstrated to have multiple values, such as building uniqueness [13], attracting target audiences [51], gaining users' trust [27], and fostering the emotional connections to users [28]. For instance, consumers tend to choose products that encompass personality traits properly matched with their own characteristics [26, 48]. Also, promoting brand personality can make website distinct from its competitors [13]. The other stream identifies how users' personality traits affect their opinions and behaviors when they interact with a design. For example, Oliveira *et al.* illuminate two points: 1) extroverts tend to use mobile phones more frequently than introverts do, 2) extroverts and conscientious people are more satisfied with their mobile phone service [41] than introverts are. Moreover, target users would consider an app more user friendly when its personality matches with those of target users [3].

Shaping the perceived personality of brands and websites can be achieved by manipulating the composition of their visual elements. In particular, the combination of visual attributes including simplicity, cohesion, contrast, density, and regularity forms e-branding personality [42]. Visual elements such as overall layout, structure, and color scheme can convey an enthusiastic or sophisticated personality for a website [45]. In addition, design asymmetry is linked to brand excitement [5]. However, there is little understanding on the assignment of mobile app personality and how users perceive the personality of mobile apps through UIs. Such research carries the potential of streamlining the understanding of mobile app adoption and success [58].

Computational Assessment for Mobile UIs

Previous attempts have highlighted the success of computationally modeling users' perception toward a design, such as visual aesthetics, first impressions, preferences, and so on [37, 38, 46, 47]. In these works, two-step data-driven approaches are commonly adopted for modeling purposes. First, they introduce automatic metrics that estimate the features of stimuli, *e.g.,* screenshots and animations. To measure webpage visual complexity, for instance, Micharlidou *et al.* look at the element-level features and compute the statistics of the webpage elements including the number of menu, images, words, and links [36]. Wu *et al.* further incorporate size, width-height ratio, colorfulness, and brightness [52]. Instead of using element-level features, Reinecke *et al.* introduce page-level measurements including average saturation color, number of leaves generated from a quadtree decomposition algorithm, and number of image areas of a website screenshot, to determine the level of colorfulness and visual complexity [46]. Miniukovich *et al.* extend this analysis to eight page-based metrics for quantifying GUI aesthetics [38]. However, most of the past works investigate a relatively small set of visual features, which cannot sufficiently depict various aspects of GUIs and thus, limits the scale of their findings. Moreover, it is unknown whether and to what extend visual features can deliver the perceived personality of mobile applications. To fill the gaps, this work explores to derive a comprehensive set of expressive features for modeling the perceived personality of mobile GUI.

Once the features of a stimuli are computed, a computational model is leveraged to predict users' perception and, more importantly, to identify the relationship between certain dimensions of the features and the prediction. Generic linear models are mostly deployed because of their high simplicity and explainability [37, 38]. For superior regression power to quantify human perception, more complex machine-learning models, such as random forest (RF) [52], support vector regressor (SVR) [23], and multi-layer perceptron (MLP) [11], have been applied by fitting data with non-linear kernels. More recently, deep learning has been utilized because of its decent learning performance [56]. In this work, we investigate the capability of different computational models for quantifying the perceived personality of mobile apps based on their UIs. Although there has been work on modeling brand perception [54, 55] or investigating the gap between the intended and perceived brand personality [32], they either study perception from text signal from social media or focus on simple visual stimuli like brand logos. We instead look into the brand personality perceived from mobile UIs.

Motivation to embody brand personality in UIs
Could you describe a mobile UI you recently designed? Would you consider the brand personality of the product? Can you provide the reasons in detail?
Design tactics for shaping brand personality
How do you tailor a GUI to convey a certain personality? What features of GUI would you consider during this procedure?
Design evaluation
How do you get feedback on your design? How do you ensure users can perceive the product in a way that you intended? Do you think whether it is possible to get reliable design assessments from a computational model?

Table 1: The sample questions asked during the interviews.

3 PRELIMINARY STUDY: EXPERT INTERVIEW

As understanding designers' practice would give us insights into how mobile user interface manifests the brand personality of an app, we conduct semi-structured interviews with five design professionals. We aim to explore designers' approaches to 1) infusing brand personality into the products they create, 2) tailoring UI design to fit target personality, and 3) getting design feedback (see sample interview questions in Table 1). We are also interested in the motivation behind their actions and the challenges encountered.

Interview Process

We invite two graphic designers (E.1 with 2.5-year and E.2 with 4-year industry experience), one product designer (E.3 with 2-year industry experience), and two visual designers (E.4-5 both with 3-year work experience) to the semi-structured interviews. We recruit them from local companies via advertisements which are posted on personal social media and word of mouth. Each interview lasts from half an hour to one hour, and is audio recorded with interviewee's consent. Two of the authors conduct thematic analysis [9]

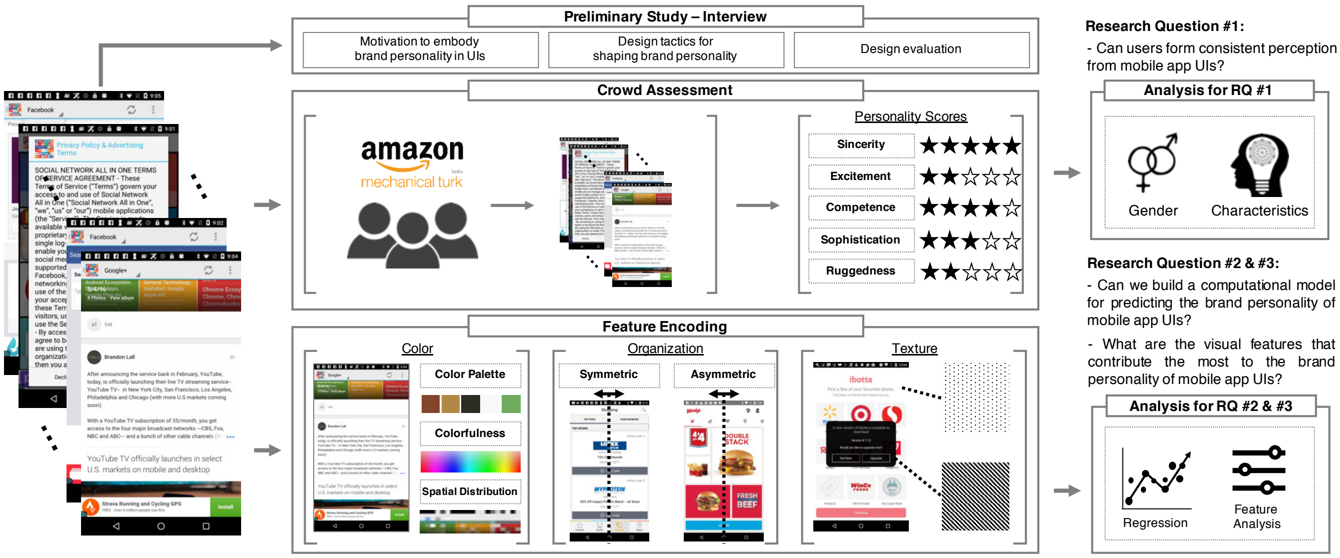


Figure 2: The workflow of the presented study. We first conduct interviews with professional designers to understand why and how they depict brand personality in mobile UI design. We then invite crowd workers to rate mobile UI screenshots regarding the perceived brand personality. We encode the screenshots by characterizing three types of visual characteristics, *i.e.,* Color, Texture, and Organization. Based on the computed features, we present a non-linear model to predict the perceived brand personality of mobile app UIs and further identify the critical visual factors contributing to the prediction.

on the interview transcripts and extract three key themes from the experts' responses: motivation, design tactics, and need for feedback.

Interview Result Analysis

Motivation. All the interviewees confirm that they take brand personality into consideration during mobile UI design, for two main reasons. 1) **Branding**. The embodiment of brand personality in mobile UIs helps establish a distinctive brand identity, promoting the recognizability of the app among similar products. As E1 reports, *"The products designed by our company often have consistent color themes to build a spirited feeling. Some of them even have exactly the same RBG values. The super-cool thing is we even developed our unique font style to make users recognize our product easily."* E3 makes a similar argument, *"It's like one would know a design might come from Apple if it has a solid gray skin and an apple-shape logo, and consider it professinal and reliable.* " Both E2 and E3 confirm that they would take other apps of the same company as design examples to keep consistent visual styles.

2) **Attracting target users**. In line with existing studies [51], the participants stress that moblie UIs communicating appropriate personalities can better engage users. Hence, they often purposely incorporate human-like characteristics and brand personality that match the persona of target users, intending to strengthen user connection to the design. As E4 mentions, *"An informal and light tone can be comfortable for users to interact with ... but it would be super weird for business use when clients require high competence."* E2 gives another example, *" if we build a music player targeted at young users, we managed to design a sporty and energetic look to give the sense of excitement."* Therefore, it is beneficial to convey an attractive, distinctive, and self-expressive brand personality in mobile UI design, in accordance with the brand identity and characteristics of the intended users.

Furthermore, they point out that personalities expressed by a mobile UI is an integration of various traits that the target audience would enjoy dealing with and that reflect the different facets of the intended brand identity. However, as E2 and E5 suggest, having a balanced mixture of the two factors, *i.e.,* matching user preference and promoting brand identity, is critical. *"We always try to make our app look unique, but overwhelming uniqueness, like too upper-class or too classic, could reduce general users' sense of belongs."* (E5).

Design tactics. The designers we interview share several techniques to embody brand personality into mobile UIs. E1 highlights the effect of color, *"I often use elegant, light and simple color tone to introduce a relaxed feeling, and dark black color for a heavy and reliable sense"*. E3 suggests *"lowercase text and round shape of buttons produce the impression of informality"*. E2 and E3 describe a two-step design process to create a consistent personality across different pages. They first set the personality of the main UI page, tuning its visual style (colors, typography, *etc.*) and characteristics of embedded UI elements (*e.g.,* button size and shape) until the theme is cohesively delivered. Then they inherit certain elements and/or style features from the main page to design secondary pages. Despite these useful tips, E1, 4, 5 comment that there is no established principles for designing UI personality. There exist standardized design guidelines to improve aesthetics (*e.g.,* in Android[1] and IOS[2]), but properly expressing personality largely relies on designers' domain knowledge and personal experiences.

Need for feedback. All participants demand for timely design feedback to ensure that their design properly conveys the intended information, which echoes the importance of review and critique during iterative design [20]. As stated by E5, *"We constantly invite real users to comment on our work and see how they feel about our design."* However, at an early development stage, most of them prefer to assess their design with a relatively small group of (senior) design professionals. As E2 mentions, *"Personally I prefer to get comments from my peers [designers] because they can provide fast feedback. User studies are useful but take much more time; and sometimes the feedback is too broad to be workable."*

Overall, our participants confirm the benefits of creating brand personality via mobile UI design. However, they all agree that there is not standard guideline for such a practice. Designers thus need fast, low-cost, actionable feedback on how well their designs communicate a target brand personality.

Research Questions

The discussion above leads us to discover the following three research questions:

- **RQ1**: Can users form consistent perception of brand personality from mobile app UIs?
- **RQ2**: Can we build a computational model for predicting the brand personality of mobile app UIs?
- **RQ3**: What are the visual features that contribute the most to the brand personality of mobile app UIs?

4 DATA COLLECTION AND PERCEIVED PERSONALITY ASSESSMENT

Data Description

Stimuli. We utilize data of 318 mobile apps from Rico[3], a dataset which collects 9,772 apps from Google Play. The selected apps are randomly sampled from the top three popular genres: business (104 apps), entertainment (106 apps), and Social & life-Style (108 apps). For each app, we randomly choose the five screenshots, which are the visual information commonly presented in the app market for each app. The screenshots are 1080×1920 pixel images in JPEG format.

Crowd Ratings. To collect the perceived personality of mobile app UIs, we recruit 542 participants on Amazon Mechanical Turk. We restrict the participants to US residents to avoid cultural differences. The participants are first asked questions on demographic information and the Big-Five personality scale. Then, the UIs of five randomly selected apps among the 318 samples are assigned to each participant to rate. After observing the five UI screenshots, each participant is required to write down five adjectives describing the given UIs. We also infer users' preferences by asking them whether they would download the presented app on a 5-point Likert scale (0 being "definitely not") after watching the presented stimuli. Then, the participants answer a standardized questionnaire with regard to their perceived personality [2]. More specifically, they need to rate the given 15 personality traits (listed in Table 2) that describe a mobile app based on its look and feel. A total of 16 questions, which include measurements for the 15 traits and one quality control question to grade the perceived personality, are presented for rating on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree" (with 0 being "strongly disagree"). We screen out unreliable responses that meet any of the following criteria: 1) contradictory answers for quality control questions, 2) meaningless written answers, 3) and answers with consistent patterns. To eliminate bias around prior familiarity, we filter out responses from users who answer that they used the given app before. We also ensure that each app receives ratings from at least five participants. Eventually, we secure 1,855 responses from 371 participants (223 males and Mean(age) = 33.54) and average the ratings from different users per application. Each valid participant is given 0.3 USD as a reward[4]. The average time for survey completion is about 15 minutes.

Human Perception Assessment

To understand users' perception of mobile UI personality, we look into the statistic details of the crowd assessment. The average interclass correlation coefficients (ICC) suggests a good agreement in user ratings on the personality measurement (ICC2k = 0.6202; 95% conf. interval is .59 to 0.96; $F(4, 19076) = 7.56$, $p<.001$). This result implies that users may hold collective judgments on brand personality given mobile app UIs **(RQ1)**.

Feedback from our expert interviews indicates that designers would like to tailor personality depiction to the target population. We thus further investigate how user characteristics, user personality and gender in particular, may impact

[1] Android Design Guidelines: https://developer.android.com/design/
[2] IOS Design Guidelines: https://developer.apple.com/design/
[3] http://rico.interactionmining.org/

[4] It is encouraged by reviewers to raise the reward to meet U.S. federal minimum wage in future studies.

the perception of mobile UIs. We focus on the extroversion dimension of user personality, because users' extrovert level is found to be correlated with their behavior towards mobile services [3]. We divide users into Extrovert (201 out of 371 users) and Introvert groups based on their answers to Big Five measurement. The results show that extroverted users have higher agreement on the brand personality ratings (ICC2k = 0.5901) than the Introvert group (ICC2k = 0.5568). Moreover, the Introvert group tends to give lower ratings ($Mean$ = 2.33 , SD = 0.98 on the 0-4 scale questionnaires) than the Extrovert group ($Mean$ = 2.65, SD = 1.05), and the difference is significant (Mann-Whitney's U Test: Z = -21.22, $p < 0.001$, r = 0.18). This result implies that extroverts tend to perceive the personality of mobile app UIs more positively compared to introverts. This is in line with findings from past research highlighting that extroverted users are more positive than introverts in product evaluation [12].

We perform similar analysis on gender (223 male participants in our study), as existing studies reveal gender difference on web interfaces evaluation [35, 46]. However, the Mann-Whitney's U test result does not show any significant effect of user gender (Z = -1.157, p = 0.118, r = 0.51), while males tend to rate the perceived personality slightly higher ($Mean$ = 2.52, SD = 1.00) than females ($Mean$ = 2.47, SD = 1.09). In contrast to the past finding which stresses the gender effect on user assessment of UIs, *e.g.,* females like colorful websites more than male [46], our study indicates that men and women may have similar perception towards the brand personality traits of mobile UIs. One possible interpretation is that the apps we pick are not gender-specific to have male and female users form different impressions.

We also explore the potential influence of perceived personality on users' app preference (measured by their rated tendency to download the applications). There is a statistical significant correlation between these two variables with a Pearson correlation coefficient of r = 0.414, $p < 0.001$. All individual brand personality traits are moderately correlated with user preference (Pearson's r > 0.3, $p < 0.05$) except the trait Tough (Pearson's r = 0.029, p = 0.653). The finding confirms the benefit of manifesting brand personality in mobile UI design for attracting potential users.

5 TOWARDS A MODEL OF PERCEIVED MOBILE APP PERSONALITY

Visual appearance has been tied to the perceived personality of design [5]. Inspired by the finding, we seek to expose the relationship between the perceived personality of mobile apps and their look and feel via a computational model. Moreover, we aim to identify what design artifacts contribute to users' perception.

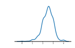
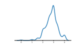
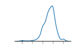
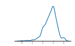
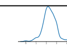
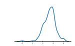
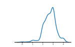
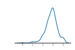
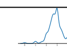
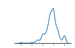
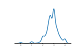
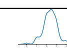
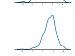
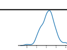
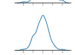
Dimensions	***Traits***	***Mean***	***Std***	***Distribution***
Sincerity	*Down to earth*	2.47	0.54	
	Honest	2.80	0.56	
	Wholesome	2.64	0.56	
	Cheerful	2.72	0.61	
Excitement	*Daring*	2.29	0.61	
	Spirited	2.65	0.57	
	Imaginative	2.68	0.60	
	Up to date	2.84	0.58	
Competence	*Reliable*	2.79	0.60	
	Intelligent	2.79	0.63	
	Successful	2.82	0.56	
Sophistication	*Upper Class*	2.37	0.68	
	Charming	2.68	0.62	
Ruggedness	*Outdoorsy*	2.18	0.70	
	Tough	1.92	0.66	

Table 2: The perceived brand personality of a mobile app is measured on five dimensions, each of which has multiple traits. Right columns show the statistical values and rating distribution of the collected data.

Computational Metrics of Mobile UIs

High-level judgments, *i.e.,* users' perception, of design have been shown to be correlated to low-level features of the appearance [8, 57]. To model the perception of mobile app personality according to the look and feel, we explore the identification of computational representations which are expressive of mobile app UIs. Prior works suggest that the aesthetic and affective responses aroused by the visual appearance of a design influence users' perception and experience [29]. We therefore scrutinize the visual features that are associated with aesthetic and affective attributes of UIs. In particular, we survey the relevant automatic metrics exploited in the prior studies and group them into color-, texture- and organization-based features.

Color-based features. Color has been found effective in evoking emotions and is linked to users' perception and responses toward a product [16, 18]. In UI design, designers often manipulate colors to deliver a certain brand personality [15], in line with the interview feedback in our preliminary study.

In this work, we characterize colors of mobile UIs from various aspects. In particular, to quantify how users perceive color, we measure the color distribution of each screenshot by computing the following features: HSV (hue, saturation and brightness) statistics, Itten contrast, W3C colors, color semantic histogram, colorfulness and dominant colors. As HSV color values are aligned with human vision system and are widely used to quantify aesthetic and affective attributes, we describe color by calculating the statistics of HSV such as mean, deviation and spread. Additionally, the effects of saturation and brightness on evoking pleasure, arousal and dominance are inferred on the basis of the formulas derived from psychological experiments [50]. Itten contrast formalizes color contrast in a way of how it induces emotion effect. We follow the implementation introduced in [33]. W3C colors measure the occurrence of the 16 basic nameable colors presented on a screenshot. This measure counts the percentage of pixels close to one of the 16 colors that are semantically recognizable to users. We also incorporate the quantification of colorfulness by analyzing the mean saturation and its standard deviation, as done in [47]. Dominant colors are measured by extracting top N (=5) occurring colors using uniform color quantification [24].

Texture-based features. Existing works have found the link between texture and visual perception. Various metrics of visual texture are examined for the effectiveness in inferring perceived complexity, aesthetics, and interestingness of visual stimuli [14, 31, 33, 39]. For example, richer texture reflects higher complexity [14] and aesthetics is linearly correlated to visual texture [31]. However, most of these metrics are tested on natural images rather than on UIs. In this work, we investigate the effects of visual texture on the perceived personality of mobile UIs. Following the practice in [31, 33], we leverage three commonly adopted metrics to describe the texture of mobile UIs, including Tamura features, Wavelet-based features, and Gray-Level Co-occurrence Matrix. Tamura texture features describe the coarseness, contrast, and directionality of images, which are related to human psychological responses to visual perceptions [31]. Wavelet-based features allow a multi-scale partitioning across three color channels, *i.e.,* HSV, via efficient wavelet transforms. In our experiment, we compute three-level transformations as suggested by [33]. Unlike the above mentioned two metrics, Gray-Level Co-occurrence Matrix (GLCM) analyzes texture information by calculating four statistical characteristics: contrast, correlation, energy, and homogeneity.

Organization-based feature. How visual elements are organized not only affects the efficiency of human mental process in perceiving visual information but also links to users' preference toward a design [6, 37], *e.g.,* users perceive symmetrical design as highly appealing [6]. To explore the different aspects of interface organization and composition, we use a quadtree decomposition algorithm to analyze a screenshot [57]. More specifically, we recursively divide a screenshot into blocks until each block reaches the threshold of the minimum entropy of color and intensity. The distribution of the blocks disclose not only the segment but also the richness of image information, as the smaller blocks would be shaped where the richer information would appear. Three attributes of the blocks: symmetry, balance, and equilibrium, are then computed to quantify the structure of the interface. Symmetry measures the symmetrical layout of the blocks along the vertical and horizontal axes. Balance calculates whether the blocks are uniformly distributed at the top and at the bottom or on the right and left. In addition to carrying out a decomposition analysis, we further investigate the elements comprising a UI. To attain the elements appearing in a screenshot, we utilize the view hierarchy information provided by [19]. The view hierarchies capture the organization of the elements, their properties, and hierarchical relationships. From this information, we identify the number of visible elements, the number of text areas, the number of image elements and the number of words.

Feature Aggregation

When analyzing the features of the five screenshots stemming from each mobile app, we need an effective aggregation strategy for encoding the features from five images into one expressive representation. The simplest way is to concatenate all the features of five images together, resulting in a single high-dimension vector. However, when the number of feature dimensions is greater than the number of samples, it might easily cause an overfitting problem. To avoid this issue, we apply an effective feature pooling technique called Vector of Locally Aggregated Descriptors (VLAD) [25]. The basic idea is to find a smaller set of features that are descriptive of representing sufficient information. To be more specific, VLAD first generates a codebook of K-cluster centers by clustering all features using K-means. Each feature is assigned to the closest cluster center, whereas the center is adjusted according to its difference to the associated features. Final representation is attained by the concatenation of cluster centers. When $K = 1$, it is equivalent to the average pooling of five screenshots, whereas $K = 5$ is equivalent to direct feature concatenation.

Computational Models

After computing the features of screenshots, we model the perceived mobile personality using regression methods. In particular, five widely-used machine learning algorithms, *i.e.,* multiple linear regression (MLR), LASSO linear regression

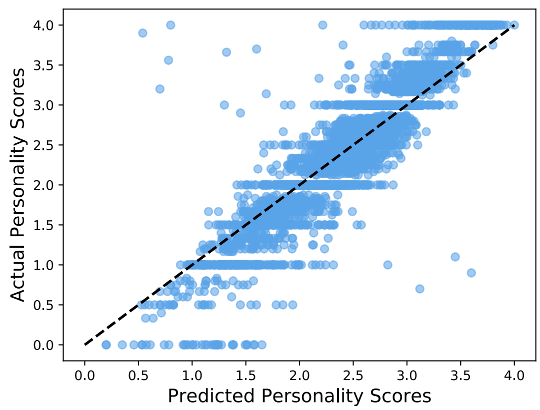


Figure 3: The predicted personality scores from the final model VS the actual personality score.

Models	MSE	R^2
Random Guess	0.135	–
Multiple Linear Regression	0.081	0.40
LASSO	0.072	0.39
Multi-layer Perceptron	0.069	0.69
Decision Tree	0.064	0.84
Random Forest	**0.035**	0.78

Table 3: Prediction performance of different regression models. MSE denotes the mean square error and R^2 is the coefficient of determination. The lower MSE and the higher R^2 score indicate better prediction performance.

(LLR), multiple-layer perceptron (MLP), decision tree (DT), and random forest (RF), are applied to predict personality scores. Among them, MLR and LLR are linear regressors, whereas the rest fit data with non-linear kernels. As there are 15 dependent variables (personality traits as shown in Table 2), we build 15 independent models for each algorithm. We adopt the metrics of mean square error (MSE) and coefficient of determination (R^2), which are commonly used in regression analysis. R^2 measures how much the model explains the variability of the whole data around its mean. We leverage the implementations of scikit-learn packages [44]. After being normalized to 0 1, the data is randomly split into 70% training set and 30% testing set. We perform 10-fold cross-validation on the training set to determine the optimal parameter settings for each model. The models' average performance on the test set is reported in the following discussion. According to the cross-validation result, we set the depth of RF as 5, the number of MLP layers as 3, the alpha of LLR as 0.000049, which yield the best prediction accuracy for the corresponding model in the validation sets. Regarding the parameter for feature aggregation, we find the model achieves the lowest MSE when $K = 5$. The overall result is reported in Table 3.

Result Analysis

First of all, we compare the five regression algorithms with random guess as a baseline. As shown in Table 3, all chosen models largely outperform random guess, which answers our **RQ2**: high-level personality judgments of mobile apps can be computationally inferred from the visual appearance of their user interfaces. Xu *et al.* reach a similar conclusion but rely on text signals from social media [54]. Although previous works have shown that linear models can to some extent describe the relationship between visual features of UIs and the perceived appeal [38], they are less effective in predicting the perceived personality. While they apply a linear regression algorithm, in our task the non-linear RF has the lowest prediction error among the five chosen algorithms. It is possibly because RF is an ensemble method that can be regarded as a combination of multiple decision trees, and thus is more robust to high-dimensional visual features and less sensitive to hyper-parameters, providing superior regression capability for our task. Figure 3 compares the RF model's prediction to the actual personality scores across all the entire dataset, revealing a strong correlation but a slight bias toward the mean. The bias occurs potentially because the actual personality scores are not uniformly distributed with a peak appearing around the mean. This implies that the extreme cases (the designs with a strong/weak personality) may be under-represented in our sample apps.

Then we examine the RF models' predictive performance across the five personality dimensions. As shown in Figure 5.b, the MSE values on Sophistication (0.040) and Ruggedness (0.042) are comparable but significantly higher than those of the other three dimensions (0.03); Wilcoxon tests $p < 0.05$. It indicates that Sincerity, Excitement, and Competence are delivered better through the look and feel of mobile UIs than Sophistication and Ruggedness. It could be explained by the users' subjective judgments of these two dimensions. To be more specific, Maehle *et al.* [34] highlight that Sophistication and Ruggedness are relatively more associated with symbolic attributes (non-product attributes) than other dimensions are. Also, *symbolic attributes* involve more subjective and intangible judgments when people perceive a product [30]. Sophistication and Ruggedness are thereby more difficult to be modeled based on the visual features.

To identify visual descriptors that contribute the most to the model, we compare the RF models trained solely on color-, texture-, organization-based features, and their combination, respectively. As noted in Figure 5.a, while the combined features boost the model the most, color-based features serve as the most informative indicator followed by texture-based features. More in-depth Gini importance [10] analysis of the

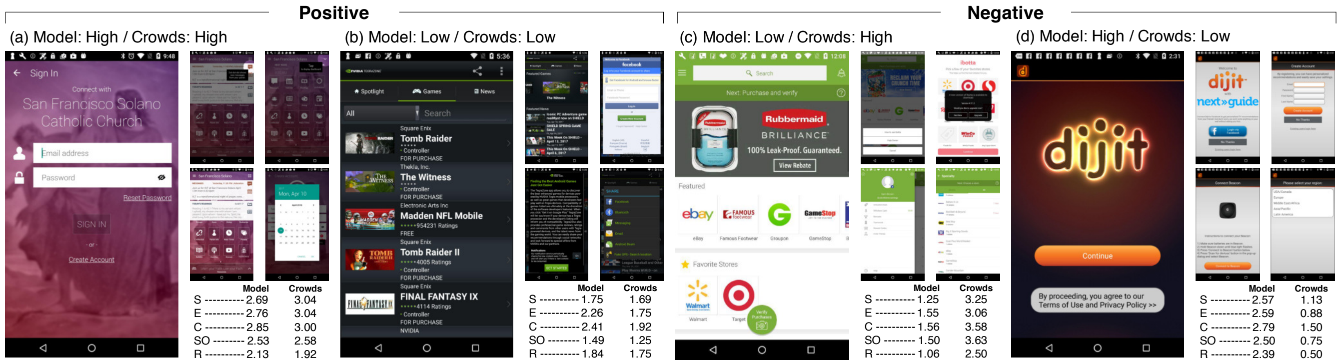


Figure 4: The sample (a) and (c) are rated positively by crowd users in terms of the perceived brand personality, whereas sample (b) and (d) have low ratings. Our model makes accurate predictions for sample (a) and (b). (c) and (d) are the examples that our model fails to predict accurately. Each alphabet at the bottom of screenshots stands for; S: Sincerity, E: Excitement, C: Competence, SO: Sophistication, and R: Ruggedness. Each number indicates the score of each brand personality dimension.

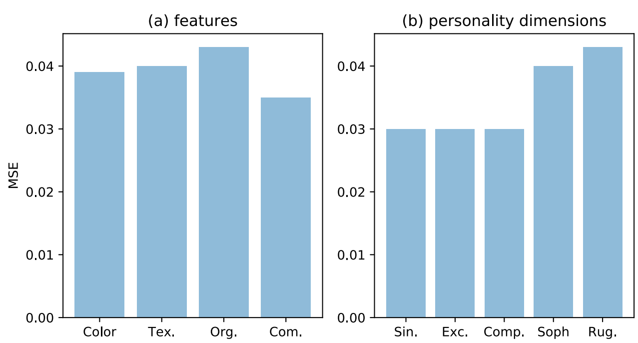


Figure 5: (a) The model performance with different features. (b) The model performance regarding different personality dimensions.

full model obtains a relative importance ranking of individual features. Figure 6 presents the top 38 essential features whose overall prediction power is comparable to that of using the full-set features. In particular, arousal of colors, colorfulness, and dominant colors are the most prominent color-related descriptors. Among organization features, the number of text areas and symmetry have relatively higher weights. This is in accordance with the previous finding that design symmetry affects perceived design personality [5]. In terms of texture features, although coarseness, contrast, and directionality are said to correlate with users' visual perception of aesthetics [31] and emotion response [33], we do not observe similar effects on the perceived personality.

6 DISCUSSION

Reflection on the Computational Model of Perceived Personality

Although our regression model achieves reasonably high prediction performance, it fails to capture certain extreme instances (mobile UIs with extremely high or low crowd ratings). Figure 4 provides two examples of negative prediction. Several factors may cause such errors. First, the model cannot fully capture mobile UI design patterns underrepresented in our dataset. For example, some applications, like Figure 4.c, display logos or advertisements on the UI pages, which might enhance brand awareness. Second, although we exploit a set of features from existing literature that effectively describe the look and feel of a mobile app, it might not adequately cover all aspect of graphical design. There could be other overlooked features contributing substantially to users' perception towards the brand personality of mobile UIs, *e.g.*, the semantics of the attached images and text. The UIs presented at Figure 1.d shows the text about terms of usage and privacy which might affect users' trust towards the app. But our features cannot capture such context. Third, as noted in Section 4, the impression of mobile UI personality traits can vary across different users, *e.g.*, extroverts have more positive impression of brand personality traits than introverts do. But the construction of our current model did not take user characteristics into consideration. We can therefore improve the model by including more diverse samples in our dataset, enriching relevant visual descriptors to train the model, and personalizing the model by leveraging user demographic profiles.

Potential applications

A direct application of our study is a design feedback system that takes one or more mobile UI screenshots as the input and generates cheap, fast, and reliable assessment of perceived personality. It is particularly helpful in the early design stage for designers to get a sense of how users would possibly

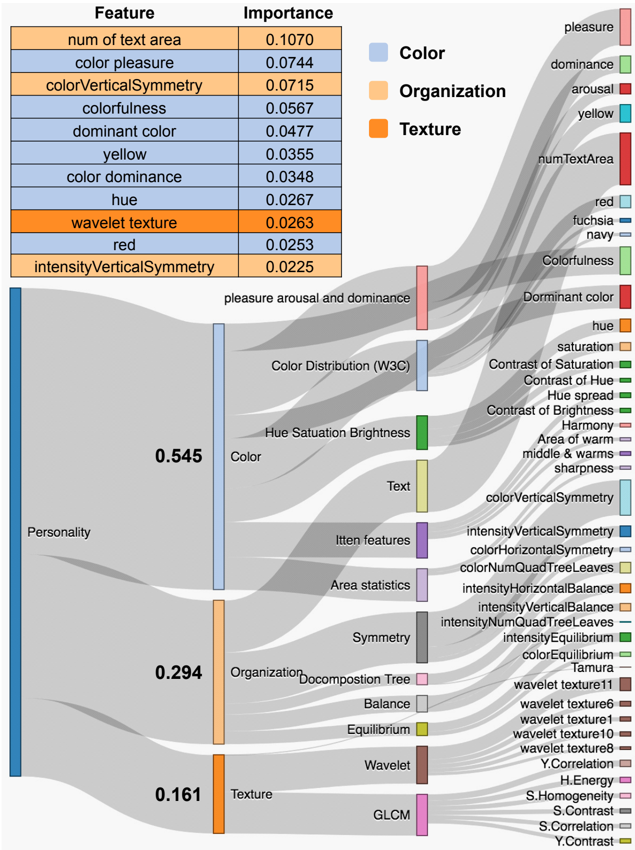


Figure 6: The relative importance of the main contributing factors to the final model in predicting brand personality. The attached numbers indicate the value of relative importance.

interpret their design from the look and feel and whether the intended message has been successfully delivered or not.

The feedback system can further identify major visual factors of the input UI(s) that impair user perception, guiding designers to manipulate visual attributes critical to brand perception and consequently reshape their design to be perceived as intended.The predicted personality score can serve as the design criterion for the objective functions in these tools and the suggested list of UI factors help narrow down the search scope of the optimization/generation algorithm. It can also support automatic UI style transformation, e.g. transferring the visual style from the main brand to the sub-brand to promote brand connection in mobile design. Moreover, when designers encounter difficulty in selecting informative, attractive, and distinctive UI screenshots to represent their app in the app store – a common challenge as noted in Section 3, our work can help recommend screenshot combinations that can achieve a high predicted score on specific personality dimensions. In all, the presented model carries the potential of being integrated as a marketing tool to reshape brand perception and facilitate brand management.

Limitation

This work has several limitations to be addressed in future research. First, our experiment only involves crowd workers from the US and we only study mobile applications from Google Play. Although such choices are necessary for reducing the number of variables in the study, they may limit the generalisability of our findings. We are aware that people from different cultural background may assess UIs differently [47] and that Android and IOS applications have different UI characteristics [38]. It would be interesting to look into how culture and system platform may affect users' perception as well as our models' performance. Secondly, we only choose applications from three most common mobile app categories. In the future, we will design a more systematic sampling strategy to guarantee the sufficient coverage and variance of the collected UIs. With a larger, more diverse dataset, we can further explore possible variations in user's perception of brand personality across different application categories. Lastly, Xu *et al.* suggest that brand personality can be predicted by symbolic attributes such as text signals [54] while we only examine the predictive power of visual characteristics of mobile UIs. In the future studies, we could exploit the user reviews from app stores to gain more insights into brand personality creation for mobile app design.

7 CONCLUSION

In this paper, we present our understanding and modeling of the perceived brand personality of mobile app UIs. We first gain insights from interviews with designers into why and how they depict brand personality in mobile UI design. Then, based on the collected crowd assessments, we confirm that users can form a consistent perception of brand personality from mobile apps' look and feel. To further model how users visually process the mobile UIs, we present a data-driven framework that compiles automatic metrics from existing literature and subsequently feed them into a non-linear prediction model. The results show that our model can predict the perceived personality of mobile app UIs with reasonably high accuracy. The model also identifies essential visual factors that contribute to users' perception of brand personality. To the best of our knowledge, this is the first work that computationally relates the perceived personality of mobile app UIs to users' visual experience. Our work can benefit designers by enabling automatic visual design assessment for creating personality-enriched mobile UI.

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