Predicting and Explaining Mobile UI Tappability with Vision Modeling and Saliency Analysis

Eldon Schoop∗
eschoop@berkeley.edu
UC Berkeley EECS
Berkeley, CA, USA

Xin Zhou
zhouxin@google.com
Google Research
Mountain View, CA, USA

Gang Li
leebird@google.com
Google Research
Mountain View, CA, USA

Zhourong Chen
czhrong@gmail.com
Google Research
Mountain View, CA, USA

Björn Hartmann
bjoern@eecs.berkeley.edu
UC Berkeley EECS
Berkeley, CA, USA

Yang Li
yangli@acm.org
Google Research
Mountain View, CA, USA

ResNet
Tappability Prediction
Tappable or Not Tappable, as perceived by users
Concatenate
\[H, W, 3\]
\[H, W, 1\]
\[H, W, 4\]
Features
512-dimensional latent representation
k-Nearest Neighbors on training dataset

Figure 1: We use a deep learning based approach to predict whether a selected element in a mobile UI screenshot will be perceived by users as tappable, based on pixels only instead of view hierarchies required by previous work. To help designers better understand model predictions and to provide more actionable design feedback than predictions alone, we additionally use ML interpretability techniques to help explain the output of our model. We use XRAI to highlight areas in the input screenshot that most strongly influence the tappability prediction for the selected region, and use k-Nearest Neighbors to present the most similar mobile UIs from the dataset with opposing influences on tappability perception.

ABSTRACT

UI designers often correct false affordances and improve the discoverability of features when users have trouble determining if elements are tappable. We contribute a novel system that models the perceived tappability of mobile UI elements with a vision-based deep neural network and helps provide design insights with dataset-level and instance-level explanations of model predictions. Our system retrieves designs from similar mobile UI examples from our dataset using the latent space of our model. We also contribute a novel use of an interpretability algorithm, XRAI, to generate a heatmap of UI elements that contribute to a given tappability prediction. Through several examples, we show how our system can help automate elements of UI usability analysis and provide insights for designers to iterate their designs. In addition, we share findings from an exploratory evaluation with professional designers to learn how AI-based tools can aid UI design and evaluation for tappability issues.

CCS CONCEPTS

Human-centered computing → Ubiquitous and mobile computing design and evaluation methods; HCI design and evaluation methods.
1 INTRODUCTION

Tapping is a fundamental gesture in mobile User Interfaces (UIs). However, because of the highly varied styles of mobile UIs, users can have difficulty telling if UI elements are tappable [37]. This harms the usability of applications, e.g., when false affordances suggest an item is tappable when it is not; or when the design of a new feature limits its discoverability.

UI designers and User Experience (UX) researchers traditionally run user studies to evaluate the usability of their designs. While these studies can provide actionable feedback and lead to significant design insights, they are often costly and time-consuming to conduct. Recent works have applied Deep Learning (DL) techniques to predict whether users will correctly estimate if mobile UI elements are tappable [37] and predict user engagement with mobile UI animations [42]. These automated approaches can help designers gain quick insights into the usability of their applications, but lack the design guidance and explanations that can be gained from controlled user studies. In addition, many automated tools rely on a functional mobile application or UIs with detailed specifications, such as view hierarchies, meaning that they may not be able to produce usable results on mockups. Yet, gaining feedback in the early stages of design is crucial.

The goal of this work is to produce a model that faithfully approximates the perception of real users for rapid, automated tappability evaluations, and a system which provides explanations of its predictions that offer insight for improving designs. To gain a basis for understanding tappability perception at scale, we create a new dataset of crowdworkers’ estimates of the tappability of UI elements in thousands of mobile UI screenshots from the RICO dataset [11]. As shown in previous work [37], human perceptions of tappability can vary significantly. To account for this, our new dataset includes 5 crowdworkers’ labels for each UI element, by which we can more reliably estimate user perceptions at scale. We use this dataset to train a purely vision-based deep neural network that, given a screenshot and a selected region of interest, predicts the perceived tappability of the selected UI element. This allows designers to rapidly assess how users may perceive elements of a mobile UI design, whether or not it is implemented in an application.

We take an important step further beyond tappability prediction by drawing upon techniques in Machine Learning (ML) interpretability and Explainable Artificial Intelligence (XAI) to explain our model’s predictions in two ways [34]. We provide a local explanation which highlights regions in the input screenshot, indicating areas the model considers most important to the tappability prediction for a given element. We provide a global explanation which uses the latent space of our model to find contrasting nearest-neighbor examples in our source dataset, allowing users to discover patterns in visually similar UIs that have opposing influences on tappability perception. To evaluate our model and its explanation outputs, we share an in-depth analysis of the behavior of our model using random examples from our source dataset, and conduct an exploratory evaluation to seek feedback from professional UI/UX designers. Specifically, this paper contributes:

- A new dataset collecting tappability labels from multiple crowdworkers per example on thousands of mobile application screenshots1. This extends previous work [37] to better address human uncertainty in tappability perception;
- A vision-based deep neural network that predicts the perceived tappability of selected UI element(s) in a mobile UI screenshot by only relying on pixels. Our model is capable of examining UI designs that are not fully specified (e.g., mockups). This significantly extends prior work since it enables a broader set of applications, e.g., to produce feedback for early-stage designs;
- A novel method for eliciting explanations of tappability predictions from our model by annotating the screen under inspection, and by surfacing similar examples from the dataset that have opposing influences on tappability perception;
- An in-depth analysis of model behavior on randomly selected examples from an evaluation dataset, and an exploratory evaluation with 13 professional UI/UX designers, from which we distill initial insights into how an AI-based tool can assist designers.

2 RELATED WORK

Our work builds on three primary areas: automated tools which assist UI designers in exploring and evaluating UIs; automated tools which assist in evaluating the usability of UIs; and algorithms and methods for interpreting the predictions of deep neural networks.

2.1 Data-Driven UI Design and Exploration

The HCI community has produced many research artifacts that help designers create UIs through the collection and use of large-scale UI datasets [27]. Datasets such as ERICA [13] and RICO [11] have enabled the creation of numerous data-driven systems in this domain. While the vast size of RICO has made it attractive for data-driven applications in research, it is known to have significant label noise [26]. Many works add annotations to RICO or take additional cleaning steps, e.g., ENRICO, which organizes RICO into design topics [24], and RICOclean which relabels icon elements in the original dataset [44]. Our work contributes a dataset that augments a cleaned subset of RICO with annotations from multiple crowdworkers predicting the tappability of various UI elements.

Designers benefit from viewing selections of varied UI design examples to serve as inspiration in the design process [38]. Gallery DC uses a neural network to tag elements in mobile UI screenshots, presenting them in a gallery to help designers explore a large set of UI element examples [7]. Other works help designers retrieve examples from datasets like RICO, e.g., from hand-drawn sketches [20], low-fidelity wireframes [9], and text-annotated layout information [2, 18, 25]. We also use the latent space of a deep

---

1We release our dataset publicly at https://github.com/google-research/google-research/tree/master/taperception.
neural network for UI retrieval. However, our model is trained on the perception of human raters, rather than to reconstruct UI layouts. This means that retrieved examples are similar in how they are perceived by humans to be tappable, rather than in visual similarity alone. In addition, our model uses the raw pixels of a mobile UI as input, allowing it to capture more detailed visual features than layouts.

2.2 Computationally Mediated UI Evaluation

Because of the cost and time involved in running controlled user studies, many systems have emerged which use heuristics, data-driven techniques, or crowdsourcing to evaluate UIs more rapidly. An early example is CogTool, which predicts task completion time 

![Image](318x560 to 558x708)

Figure 2: The type distribution for the 18,667 labeled UI elements. Blue and white splits show the proportion of leaf and inner elements in the view hierarchy.

In our work, we use the latent space of our model to retrieve similar examples from our dataset, a known technique for describing model predictions by using other examples [31]. We split retrieved UIs into contrasting examples [5] by their tappability prediction. This exposes designers to similar UI elements with differing effects on perception, a technique based on the variation theory of learning [10].

3 CROWDSOURCING PERCEIVED TAPPABILITY FROM SCREENSHOTS

Similar to [37], we perform a tappability study on a large set of UI elements in Android mobile app screens. The raters are given a screenshot from the screen set with one of the elements highlighted, and indicate whether the UI element is tappable or not. Each UI element is labeled by 5 different raters. Each worker completed up to 90 UI elements, with a median of 30.

We collect 18667 unique UI elements from 3218 screens from the RICO dataset [11]. In the view hierarchy of each screen, we select up to five unique clickable and non-clickable elements for labeling. Similar to [44], we asked crowdworkers to discard examples whose bounding boxes were not aligned with underlying UI elements. The same filter rules are applied as [37]: we (1) choose top-level clickable elements starting from leaves and, (2) avoid choosing the children of already-chosen non-clickable elements.

There are 24 different types of collected elements, 77% of which are leaves in their corresponding view hierarchy trees (Figure 2). By analyzing the labels and the screens, we notice that some UI elements are labeled with high agreement, but others are not (Table 1). For 44.4% of UI elements, 5 raters agreed unanimously. However, 24.1% of UI elements were ambiguous to raters, i.e., at most 3 agreed on a label. Nonetheless, as each element is inspected by multiple raters, our dataset has more precise labels about human tappability perception than prior work, which is desirable for machine learning tasks and data analysis. Our dataset also reveals UI elements that are indeed ambiguous, for future analysis. For model training in this work, we randomly split the dataset into 80% of the UI elements for training, 10% for validation to tune hyperparameters, and 10%
we feed the entire RGB screenshot to the model along an additional convolutional Neural Network (CNN) model for tappability prediction. The problem statement for our model is: given an input screenshot, a binary mask $M$ is to crop the target element's pixels from $I$ (screen height and width, and 3 is the number of channels (i.e., RGB)). Let $(x_{min}, y_{min})$ and $(x_{max}, y_{max})$ denote the top-left and bottom-right corner coordinates of a target UI element bounding box respectively.

A naive implementation of using CNNs for learning tappability is to crop the target element's pixels from $I$ and feed them to a CNN. However, this discards important contextual information in the screen, making it difficult to learn an effective model. Instead, we feed the entire RGB screenshot to the model along an additional mask channel in the input. For a given element, we first create a binary mask $M \in \{0, 1\}^{h \times w}$, using $i$ and $j$ as row and column indices, respectively:

$$M_{ij} = \begin{cases} 1, & \text{if } y_{min} < i < y_{max} \text{ and } x_{min} < j < x_{max} \\ 0, & \text{otherwise} \end{cases}$$

In other words, the entries corresponding to the target element’s pixels are 1’s and the others are 0’s in the binary mask. We then concatenate $I$ and $M$ along the channel dimension to form the input to the model: $I' = [I, M]$ of shape $[h, w, 4]$. To the model, $I$ provides pixel information of the whole screen, while $M$ indicates the screen area for which the model should predict tappability (Figure 1).

Specifically, our model is a ResNet-18 [17], modified to accept a larger input image with a dimension of 960 by 540 (to accommodate mobile UI screenshots) along with the corresponding binary mask. The model outputs softmax probabilities for two classes: tappable, or not tappable. We train our model on the training set by minimizing cross-entropy loss, using Stochastic Gradient Descent with Nesterov momentum, with a learning rate of 0.05 and a batch size of 1024, for 1500 epochs. Our learning rate decayed by an order of magnitude (dividing by 10), after epochs 100, 500, 1000, and 1300. We evaluated how well our model predicted user perceptions of the tappability of UI elements with our test set. Our model achieved a precision of 91.54% and recall of 80.23% with a decision threshold of 50%, and AUC of 0.9030.

To compare the performance of our model to previous work in tappability prediction, we replicated the model from Swearngin et al. [37] and benchmarked this model on our new dataset in two separate configurations: by using all of its input features (screenshot pixels, region pixels, component text, component type, and intended tappability), and by using pixels only (from the screenshot and region). Our model, which only uses pixels, clearly outperforms the replicated model [37] when it only runs on pixels. When the replicated model uses all input features, including those from the view hierarchy, on our dataset, our model achieves better AUC and similar precision, but has slightly lower recall when using a 0.5 decision boundary (Table 2). The slightly lower recall of our model is likely due to the distribution of tappable elements in our dataset, which can be addressed by fine-tuning the decision threshold.

**5 EXPLAINING TAPABILITY PREDICTIONS**

Our neural network can be used to model users’ perceptions of tappability for a broad variety of mobile UI elements. However, the predictions of models like ours are limited in the sense that designers must rely on their own judgment to determine what visual cues were responsible for the prediction, and, if needed, how the design must be modified to improve its perception (Figure 3). We draw upon techniques from XAI and ML interpretability to provide deeper explanations of our model’s predictions, both in the context of the input itself, as well as examples the model has learned from. We implement two types of explanations: at the local level, to suggest which elements in the input screenshot were most influential, or “salient”, to a given prediction, and at the global level, to show how other applications with similar design patterns can influence tappability perception positively and negatively.

| # of workers for agreement | # of UI elements | ratio |
|---------------------------|------------------|-------|
| 3-agreement               | 4508             | 24.1% |
| 4-agreement               | 5872             | 31.5% |
| 5-agreement               | 8287             | 44.4% |

Table 1: Agreement of tappability for the 18,667 labeled UI elements.
Table 2: Tappability prediction model performance on our new dataset. Our model, which only uses pixels, clearly outperforms [37] when only run on pixels. It has slightly higher AUC, similar precision, and slightly lower recall compared to the all-features replicated model.

| Model                                         | AUC   | Precision (%) | Recall (%) |
|-----------------------------------------------|-------|---------------|------------|
| Ours (pixels only)                            | 0.9030| 91.54         | 80.23      |
| Swearngin et al. [37]; pixels + all other features | 0.8437| 91.65         | 84.53      |
| Swearngin et al. [37]; pixels only            | 0.6521| 76.79         | 80.79      |

Figure 3: The input to our model as a running example to this section, a randomly selected screenshot from our dataset. The element of interest is indicated as a magenta dashed rectangle. Our model predicts the element is tappable with a probability of 57.85%.

Figure 4: Left: The same input screenshot as in Figure 3 with a selected element in a magenta dashed rectangle. Center: the heatmap generated by XRAI, using regions from UI elements. The regions which most strongly influence the selected element’s tappability prediction are rendered in red, while the least influential regions are rendered in blue. Some text is extremely highly attributed (an anomaly). Right: the input screenshot filtered by the values of the saliency heatmap. The elements most important to the tappability prediction are the brightest.

Figure 5: Center: the same XRAI calculation as in Figure 4, but without using provided regions from the UI element bounding boxes. Regions are generated using Felzenszwalb segmentation.

5.1 Attributing Tappable UI Elements with Saliency Techniques

To provide a local explanation of the model’s predictions, we use the XRAI algorithm [21], a gradient-based algorithm which produces a heatmap highlighting what regions of an input image were the most influential to a given model output, also known as a saliency map (Figure 4). Importantly, while the output of saliency algorithms like XRAI are correlative, and cannot explain the causal reasons behind model predictions, they are often useful for gaining a better understanding of model behavior in many applications [1]. In our use case, we use XRAI to generate a heatmap of the UI components in a mobile app screenshot that most strongly influence the tappability prediction for a particular element. XRAI calculations and heatmaps are particular to the specified UI element in a tappability prediction, since predictions for different UI elements can depend on their particular context and relationship to other UI elements. Designers can use the XRAI heatmap to see when the perceived tappability of a particular element is heavily influenced by other regions on the screen, e.g., how introducing a new component changes the perception of surrounding elements.

The XRAI algorithm works by first oversampling the input image into overlapping superpixels of different sizes. Next, Integrated Gradients, a pixel-based attribution method [36], is calculated on the input image from black and white baselines. These pixel-level attributions are then aggregated by summing over segments, ranking segments from most to least important, and merging them up to a selected threshold. We make one key modification to the XRAI technique. Rather than oversample the image using Felzenszwalb segmentation, we use the native bounding boxes of mobile UI elements if they are available or can be specified. This means
we can directly summarize model attributions for regions corresponding to mobile UI widgets, reducing the noise from automated segmentation methods (Figure 5).

5.2 Explaining Predictions with Similar Contrasting Examples

Our global explanation method situates the given prediction in the context of retrieved examples from our mobile UI dataset. We use nearest neighbors on embeddings from our model to find examples the model considers similar. The model’s embeddings capture visual similarity, and the rough position and size of the input bounding box (see section 6). These nearest neighbors are then split by the model’s tappability prediction, creating a contrasting explanation [5]—a visualization of a set of UIs that have similar designs to the input, but opposing influences on the perception of tappability. This acts as a set of curated examples for design inspiration to help designers make changes that affect users’ tappability perceptions of UI elements (Figure 6).

To capture embeddings from our neural network, we take the output from its final convolutional layer and flatten it into a 512-dimensional vector. We precompute embeddings for every mobile UI example in our source dataset, and split them into two separate indexed arrays of predicted tappable and nontappable examples. To filter out potentially confusing or ambiguous examples, we limit these lists to examples which have >65% and <35% tappability probabilities, per our model’s predictions. In practice, we found that splitting based on model predictions produces more consistent results than ground-truth human labels. We use the NearestNeighbors learner from the sklearn Python package to search for the 5 nearest neighbors from each list (showing 10 examples total), to embeddings from an input image.

6 ANALYSIS OF SELECTED EXAMPLES

In this section, we sample real-world screenshots from our dataset to show how our model performs and what our explanations capture. We randomly select four elements from our dataset that have associated regions corresponding to common Android UI leaf elements: ImageView, Button, TextView, and EditText. For each of these inputs, we show the output of our model and explanation methods, and describe what could be inferred about the behavior of our model. In section 8, we summarize trends apparent in our model across examples and discuss their implications and opportunities for future work.

6.1 ImageView: Food App Header Logo

This randomly-selected UI and element is a screenshot from a food application, presenting a complex login view with many clickable buttons and graphics. The selected region paired with this UI screenshot is a logo placed above the login form. The model predicts this element is not tappable, with a 10.01% tap probability.

The XRAI heatmap strongly attributes the input element as important to its tappability prediction, and does not factor other elements in the screen much. It is possible that, since the input element is a graphic, the model does not consider surrounding elements a significant factor. Combined with the relatively high model confidence, we can assume that properties of the input element itself (its

![Figure 6: Nearest neighbors to the input screenshot from Figure 3, split by tappability predictions. Examples the model predicts as tappable are on the left, with non-tappable examples on the right. Examples contain an entire screenshot with a specified region, and the region in a larger view. Columns are sorted by distance to the original input in the model’s latent space (most similar on top).](image-url)
 appearance or position) strongly signify non-tappability on their own. This means that making significant changes to other elements on the screen would likely not impact the perceived tappability of this element.

Most nearest neighbors of the food app also contain graphical elements and icons, with the exception of large text objects that have similar locations and sizes on the screen as the input (Figure 8). The non tappable elements are generally larger, and closer to the center of the screen, matching the style of the input. Tappable elements tend to be icons commonly associated with actions, e.g., a shopping cart and an ‘X’ to close a dialog.

### 6.2 Button: Health App Card Button

This element is a screenshot from a health application, presenting a complex view with a card, image, and list. The selected region paired with this UI screenshot is a “Dismiss” button within a card. The model predicts this element is tappable, with a 99.07% tap probability (Figure 9).

Similar to the ImageView example, the XRAI heatmap most strongly illuminates the input element itself. This is likely because the model has learned to associate Material Design buttons with a strong perception of tappability, and does not need to reference much context to establish a confident prediction. The attributed text in the screen’s title card (“Learn”) may suggest the model’s attention to a common Material UI standard.

Tappable neighbors are entirely buttons and tabs with overlaid text and high tappability scores. Non-tappable neighbors are more mixed, including descriptive text, icons, and even images. The predictions for several non-tappable examples disagree with the underlying raters’ labels (Figure 10). The noise in the non-tappable examples could be a limitation of discretizing the neighbors by tappability prediction, an effect discussed further in subsection 8.3.

### 6.3 TextView: Finance App List Item

This example is a screenshot from a finance app, with a view presenting a chart and pricing details of a stock (Figure 11). The selected region paired with this UI screenshot is a text field displaying a

---

**Figure 8:** Nearest neighbors from subsection 6.1, split by thresholded model predictions (tappable neighbors on the left). Many neighbors (both tappable and not) are graphical (icons and drawings). Tappable elements tend to be smaller, and situated near the edges of other elements. Non tappable elements are generally larger, and closer to the center of the screen.
Figure 9: Example from subsection 6.2. Left: input screenshot with a Button element selected, annotated with a magenta dashed rectangle. Center Left: Close-up view of the selected UI element. The model predicts it is tappable, with a 99.07% tappability probability. Center Right: The XRAI heatmap most strongly illuminates the input element itself. This is likely because the model has learned to associate Material Design buttons with perceptions of tappability, and does not need to reference much context to establish a confident prediction. Right: the input screenshot filtered by the values of the saliency heatmap.

The model predicts this element is not tappable, with a 36.38% tap probability.

The XRAI heatmap strongly illuminates the region itself, while also strongly highlighting text in tab navigation and an icon adjacent to a nearby text view. Although the input region is generally expected to be the most important element for its own prediction, one element of tab text is highly attributed, an anomaly. This may be due to variances in TextView tappability when below navigation tabs. It is also worth noting that surrounding text views are lightly attributed as well, suggesting the model has factored some surrounding context into the input element’s prediction.

All nearest neighbors of this input screenshot share strong visual similarities with the input (text on a light background), but appear in different contexts (Figure 12). Many tappable elements have icons or graphics nearby, which possibly serve as signifiers of the tappability of the adjacent text. Non tappable elements have brighter text, and are often placed as descriptions next to tappable elements. It is worth noting that many tappable elements are also ListView, 2 of which have similar color schemes, indicating the model is factoring multiple contextual elements within the input example besides the region itself.

6.4 EditText: Entertainment App Login Field

This element is a screenshot from an entertainment application, a simple login view. The selected region paired with this UI screenshot is a “Password” text field. The model predicts this element is tappable, with a 99.47% tap probability (Figure 9).

Like previous examples, the XRAI heatmap strongly attributes the selected EditText view, and does not attribute other elements on the screen. Similar to the Button example, it is possible that the model has learned an association between the Material UI EditText component and strong perceptions of tappability.

The image in this view does not appear to be attributed differently from the entire login card. While it is likely that the model determined the image is not a signifier of tappability, it could also

Figure 10: Nearest neighbors for subsection 6.2, split by thresholded model predictions (tappable neighbors on the left). While many tappable elements contain similarly-styled buttons from other apps, the non-tappable elements display highly varied elements, with and without text. A potential cause of this is that most elements near the input button in latent space are other buttons; and the nearest non-tappable examples are significantly further away, so they are not as visually similar.
be, in part, due to these two being the same actual element in the source UI view hierarchy. Our use of XRAI is limited by the bounding boxes provided from the source UI view structure—large objects in UIs may cause XRAI to aggregate too much detail from pixel attributions beneath. In practice, this may not be a significant limitation, since many large UI objects inherit a single tappability attribute.

Like the TextView example, the tappable neighbors are all visually similar, with text over a light-colored background, comprising buttons and text fields. Non-tappable neighbors are, similarly, text elements in different contexts: descriptions of nearby objects, instructions, or hyperlinks. Of note, the third non-tappable neighbor is also an EditText element. A probable distinguishing feature of this element is that the text is dark (not grayed), and thus the model could be confusing this element for a text description (Figure 14).

7 EXPLORATORY EVALUATION WITH PROFESSIONAL DESIGNERS

To better understand how our model and its explanation outputs can be used in design practice, we conducted an exploratory evaluation with professional UI/UX designers, and analyzed the successes and drawbacks of our approach.

7.1 Participants & Study Design

We recruited 14 participants at a large technology company. We excluded one participant’s results from analysis because they did not submit any written feedback. These participants were from multiple teams and had an average 11 years (standard dev. 7.5 years) of professional UI/UX design experience. To capture a variety of scenarios, we randomly selected six UI examples (mobile app screenshots with a preselected UI element) from our dataset for review. Input UIs and predictions are shown in Figure 15, outputs from explanation algorithms are shown in Appendix A. Examples counterbalanced prediction (tappable/non-tappable), prediction confidence (high: > 0.85; low: < 0.15), and rater (worker) agreement (high: 5-rater
agreement; low: split 2-3 in either direction). We selected the tap-
pable/high confidence/high agreement example for use in onboard-
ing. Tappability labels from raters associated with the examples
were not shown to participants. Our study plan was reviewed by
our company’s legal and privacy boards, and participants were
required to give informed consent before trials.

During each session, we first described our model and its ex-
planation outputs using the onboarding example. Then, the five
remaining examples were shown in a randomized order, together
with the model’s outputs. For each example, we asked our partic-
ipants to think out loud; reflect on whether they understood or
agreed with the model’s outputs; and suggest how the selected
element in the example could be altered to influence its perceived
tappability. We explicitly informed participants that both positive
and negative feedback would be useful to the design team for mak-
ing improvements. A researcher took notes of verbal responses
while examples were shown. After seeing all examples, participants
filled out a short survey asking what they thought performed well,
needed improvement, and could fit into their design practice. An
tire session took approximately 45 minutes to complete. For anal-
ysis, feedback from written responses was processed in an open
coding phase, and further grouped by one researcher into the related
topics, which were agreed upon with the other researchers [39].
Quotes shared below are exclusively from survey responses.

7.2 Results

7.2.1 Tappability predictions can save significant time and effort
compared to user studies. From survey responses, 11 participants
perceived the system as accurate, and 7 remarked how the system
would be valuable for evaluating designs as a time-saving alter-
native to running user studies: “It’s fairly accurate in predicting
whether an element is tappable or not” (P7); “I think it’s great to see
a quantified results of tappability - it can reduce the time to conduct
usability study.” (P6); “UI designers could use the model to cross check
and see if they match the anticipated results. If that happens, it will
save a lot of time running user studies.” (P3). One noteworthy theme
was the value of using our system for rapid evaluations at multiple
stages of the design process: “It might be useful during handoff to

![Figure 13: Example from subsection 6.4. Left: input screen-
shot with a EditText element selected, annotated with a ma-
genta dashed rectangle. Center Left: Close-up view of the
selected UI element. The model predicts it is tappable, with
a 99.47% tappability probability. Center Right: The XRAI
heatmap strongly attributes the EditText view, and does
not attribute other elements on the screen. Right: the input
screenshot filtered by the values of the saliency heatmap.]

![Figure 14: Nearest neighbors from subsection 6.4, split by
thresholded model predictions (tappable neighbors on the
left). The tappable neighbors are highly visually similar, al-
though they are not all the same input type as the input
(many are buttons with a light background).]
7.2.2 Analysis of a single screen offers limited notion of context in a UI flow. While many participants remarked on the model’s generally good performance, 4 were more critical or skeptical when it came to UI elements that were sensitive to the context of other screens in a UI flow, e.g.: “It doesn’t seem as useful for navigation or text where the tappability is more contextual” (P4); “Considering context and looking at the whole page holistically are very important in UI design. The system tend to ignore the context of the screen.”

E.g. Is it the home screen or interior page? The app logo can be tappable depending on the context” (P13). The cases referred to in these quotes are examples with low model confidence, reflecting a potentially ambiguous perception of tappability that depends on how the input screenshot is situated in a flow of multiple UIs. One limitation of our model is that it only uses a static snapshot of a UI as input. In future work, temporal information could be used in our model’s inputs to add additional context, as prior work has done for predicting user engagement with animations [42] and grounding UI action sequences [26]. In addition, this is a case where including additional input modalities (e.g., text) can provide additional cues to boost prediction confidence.

7.2.3 Contrasting similar examples provided design feedback for iteration. At least 5 participants wrote favorably of the contrasting similar examples in open-ended feedback, and remarked on their value for inspiring potential design changes: “The initial ‘Model tap prob’ metric is extremely useful as are the examples of similar UI elements that have both low and high [tappability] scores.” (P14); “I might also use some of the comps [examples] to find inspirations on other ways to design a certain element” (P9). Some participants liked the diversity of some sets of contrasting similar examples (“the provided examples are useful to reference and compare to, even if the similar elements are not exactly the same.” (P10)), while others desired a greater degree of semantic similarity (“Heading component compares to a CTA button in Settings page. It feels like comparing apples to oranges. I would suggest, using similar UI component proximity for similar examples” (P1)). One direction for future work could be to allow users to filter and set thresholds for examples (e.g., by certain types or locations of UI elements), or reporting actual distances (“Maybe for the nearest neighbors, provide some indications of how near or far the neighbor is, e.g., 90% vs 10%” (P12)).

Overall, this feedback suggests that the contrasting similar examples, curated based on a specified UI element, have the potential to provide useful inspiration for designers. This may help “close the loop” beyond tappability prediction scores alone.

7.2.4 Participants desire more explicit explanations beyond the heatmap. While 2 participants remarked that the heatmap was useful, 4 participants noted the heatmap was confusing to use, or needed better instructions, e.g.: “Heat map. Confused me and would need some guidance on how to process the info.” (P14); “Saliency heatmap definitely needs some mental shift to understand.” (P6). While this could potentially be mitigated with improved onboarding or more experience [6, 43], the “black-box” nature of our model means, while it may be effective at predicting users’ perceptions of tappability, the mechanisms which enable those predictions may not reflect the same reasoning as users [28]. The mismatch in mental models could explain this result: “I found the heat maps and nearest neighbors less helpful because they didn’t resemble my own mental model / instincts for evaluating the usability of these mockups” (P4).

Some participants expressed a desire for deeper explanations of why certain elements in the heatmap contribute to a tappability prediction more than others, which could help improve its usability: “On the heat map, add some explanation about why the other elements might or might not impact the probability score of an element” (P14); and others wished the system could output design suggestions directly: “It’d be amazing if the system can provide recommendation..."
like boost the color contrast" (P6). One promising direction for future work could draw from techniques in ML debugging research, by identifying common “heuristics” from patterns in the model’s and XRAI heatmap’s outputs and raising messages with concrete design suggestions (e.g., increasing contrast or changing colors) [19, 33].

8 THEMES IN MODEL BEHAVIOR: DISCUSSION AND LIMITATIONS

In this section, we describe patterns observed in our selected examples and discuss implications for the use of our model and explanation mechanisms.

8.1 Persistent Signals and Signifiers

Text as a feature indicating tappability. In examples in section 6 as well as examples in our user evaluation, bounding boxes surrounding text elements were highly attributed by XRAI. This does not necessarily mean the text itself is perceived as tappable, but rather that the existence of text serves as a signifier of tappability to nearby elements (see subsection 8.2). This is one potential drawback to our pixel-based model compared to multimodal models that use text as input to gain a deeper understanding of an element’s context (e.g., a “submit” button or “click here to unsubscribe” text).

Icons next to text generally indicate tappable regions. To our model, small icons or graphics appearing next to text strongly signify tappability. This is demonstrated in Figure 12, where most tappable text elements are near radio buttons, icons, and other graphics. Using icons to signify the tappability of adjacent text elements is a well-known practice [29]. However, our model does not always produce reliable tappability predictions of checkbox elements (E.g., Figure 12, bottom right). This is likely due to ambiguity in the labeling task. Since the checkbox, accompanying description, and parent element containing both are each distinct UI elements with separate bounding boxes, any one of these elements within a given screenshot could be selected for labeling. Crowdsources may have different perceptions of the tappability of the different elements, and this uncertainty is reflected in our model’s prediction scores.

Image views in apps are not consistent predictors. Because the content of ImageView elements can be highly varied (e.g., containing icons, logos, thumbnails, previews, ...), they can sometimes confound our purely vision-based model (see Figure 10). While our model likely also uses the location and context of the image element, the content of the image can overwhelm predictions, possibly due to the texture sensitivity of CNNs [15]. One way to potentially mitigate this effect would be to replace images with placeholders, similar to wireframes [9, 11].

8.2 Challenges in Interpreting XRAI Attributions

XRAI attributions highlight influential regions; highly influential regions are not necessarily tappable themselves. As reflected in the results of our user evaluation, the XRAI heatmaps require practice to take full advantage of, and could benefit from the addition of heuristic-based explanations. A critical note for our use of XRAI is that the heatmap it produces is not a tappability heatmap, but a heatmap showing how regions in the UI screen influence the tappability prediction for a particular element. For example, if highly attributed text near a button was removed, that button would likely no longer be classified as tappable. As such, saliency methods like XRAI are often useful in practice for diagnosing the features that influence predictions, and the sensitivity of that prediction to contextual factors.

Summarizing attributions with regions may leave out important details. In contrast to XRAI, which uses regions, pixel-based saliency methods like Integrated Gradients [36] highlight inputs at a finer scale. While this may be useful for debugging features of small UI elements, pixel-based methods are known to be difficult to interpret by humans compared to region-based methods, and can be susceptible to errors [1, 21].

XRAI attribution values cannot be compared between examples. Like other gradient-based saliency methods, the raw values of XRAI attributions are specific to input examples [1]. Some other algorithms, such as DeepSHAP [30], sum to the probabilities of predictions, and may be compared between examples. These other methods could also enable new interactions, such as aggregated analyses, a promising direction for future work.

8.3 Browsing Nearest Neighbor Examples

Nearest Neighbors capture many dimensions of similarity. Across all of our examples, nearest neighbors appear to capture dimensions beyond visual similarity alone. In particular, bounding box locations, sizes, and aspect ratios are generally similar among neighbors. This indicates that our model has not only learned to use the appearance of an element to predict its tappability, but also contextual information such as its location, shape, and proximity to other elements. As participants in our user evaluation noted, adding interactivity to the nearest neighbor examples, such as the ability to filter and sort by component types and application properties, could help narrow down these contextual cues to provide more relevant feedback for iterating UI designs.

Splitting neighbors by binary tappability predictions discards some information. While using a discrete boundary can provide useful contrasting examples, the average tappability prediction probabilities and distances between splits can contain subtle yet important information about the landscape of UI design patterns related to the input. For example, the health app’s non-tappable neighbors included many seemingly unrelated graphics. This may be because of skewed distances, i.e., most nearby examples are tappable, and the closest non-tappable neighbors are significantly further away, and, thus, less similar. In other cases, the sets of neighbors may have skewed average probabilities (e.g., near 99% for tappable, and near 49% for non-tappable). This is an additional, strong, indicator that similar UIs are generally either perceived as tappable or uncertain, rather than non-tappable. The contrary is also true: the neighbors of confidently non-tappable examples often score near 51% for tappable, and 0% for non-tappable. In future work, these details could be made explicit in more continuous, interactive visualizations, to help designers explore related UI designs.
Encouraging exploration of neighboring examples. While using UIs with similar designs but different effects on tappability perception are useful for contrastive explanations, designers often value seeing diverse examples of designs for inspiration [9, 38]. Future iterations of this work could sample more distant UI examples, filtered by UI element types, or even learned concepts, i.e., with concept vectors [22]. In addition, since nearest neighbor examples are split by model predictions, the similar examples do not have to be limited to our source dataset. In other words, our model can be used to retrieve nearest neighbors or similar examples from other datasets.

8.4 Additional Limitations

Concept drift. While UI design styles and trends change over time, our model is trained on a “static” snapshot of application UIs, and may give less reliable predictions over time. This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

Perceived tappability predictions contain multiple signals. As we have found by analyzing the distribution of label agreement in our dataset, the tappability of many UI elements in the wild appear ambiguous to users. While this uncertainty explicitly limits the possible accuracy of our model, it also means that predictions near the decision boundary suggest user confusion. This signal, along with other usability metrics (e.g., engagement [42] or cognitive load) may be useful outputs for future models.

9 CONCLUSION

We presented a novel, automated system for predicting the human perceived tappability of mobile UI elements and explaining model predictions to users. Our work significantly advanced the art by developing a purely vision-based deep neural network, which only relies on pixels and does not require a UI to be fully specified; and by enabling mechanisms for explaining design insights to the user with contextual and instance-level interpretations of model predictions. We also create a new tappability dataset where each user with contextual and instance-level interpretations of model and by enabling mechanisms for explaining design insights to the user. This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

We presented a novel, automated system for predicting the human perceived tappability of mobile UI elements and explaining model predictions to users. Our work significantly advanced the art by developing a purely vision-based deep neural network, which only relies on pixels and does not require a UI to be fully specified; and by enabling mechanisms for explaining design insights to the user. This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

We presented a novel, automated system for predicting the human perceived tappability of mobile UI elements and explaining model predictions to users. Our work significantly advanced the art by developing a purely vision-based deep neural network, which only relies on pixels and does not require a UI to be fully specified; and by enabling mechanisms for explaining design insights to the user. This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.

This phenomenon is known as concept drift [40], and may be mitigated by augmenting the dataset with new examples over time. Furthermore, since our dataset comprises only Android applications, our model may require fine-tuning to generalize well to UI screenshots from other platforms.
CHI ’22, April 29-May 5, 2022, New Orleans, LA, USA

Eldon Schoop, Xin Zhou, Gang Li, Zhourong Chen, Bjorn Hartmann, and Yang Li

[41] Jason Wu, Xiaoyi Zhang, Jeffrey Nichols, and Jeffrey P. Bigham. 2021. Screen Parsing: Towards Reverse Engineering of UI Models from Screenshots. CoRR abs/2109.08763 (2021). arXiv:2109.08763 https://arxiv.org/abs/2109.08763

[42] Ziming Wu, Yulun Jiang, Yiding Liu, and Xiaojun Ma. 2020. Predicting and Diagnosing User Engagement with Mobile UI Animation via a Data-Driven Approach. In Proceedings of the 2018 Designing Interactive Systems Conference (Hong Kong, China) (DIS ’18). Association for Computing Machinery, New York, NY, USA, 585–596. https://doi.org/10.1145/3196709.3196730

[43] Xiaoxue Yang, Ying Xu, and Jindong Chen. 2021. Multimodal Icon Annotation For Mobile Applications. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3447526.3472064

[44] Xiaoyi Zhang, Lilian de Greef, Amanda Swearngin, Samuel White, Kyle Murray, Lisa Yu, Qi Shan, Jeffrey Nichols, Jason Wu, Chris Fleisch, Aaron Evertt, and Jeffrey P. Bigham. 2021. Screen Recognition: Creating Accessibility Metadata for Mobile Applications from Pixels. Association for Computing Machinery, New York, NY, USA. http://doi.org/10.1145/3411764.3445186

[21] Andrei Kapishnikov, Tolga Bolumbas, Fernanda Viégas, and Michael Terry. 2019. XRAI: Better Attributions Through Regions. In 2019 IEEE/CVF International Conference on Computer Vision (ICCV). IEEE, 4947–4956. https://doi.org/10.1109/ICCV.2019.00505

[22] Been Kim, Martin Wattenberg, Justin Gilmer, Carrie J. Cai, James Wexler, Fernanda B. Viégas, and Rory Suyres. 2018. Interpretability Beyond Feature Attribution: Quantitative Testing with Concept Activation Vectors (TCAV). In Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10–15, 2018 (Proceedings of Machine Learning Research, Vol. 80), Jennifer G. Dy and Andreas Krause (Eds.). PMLR, 2673–2682. http://proceedings.mlr.press/v80/kim18d.html

[23] Chunggi Lee, Sanghoon Kim, Dongyun Han, Hongjun Yang, Young-Woo Park, Bum Chul Kwon, and Sungahn Ko. 2020. GUComp: A GUI Design Assistant with Real-Time, Multi-Faceted Feedback. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376327

[24] Luís A. Leiva, Aashish Hota, and Anitul Oulavirta. 2020. Enrico: A Dataset for Topic Modeling of Mobile UI Designs. In 22nd International Conference on Human-Computer Interaction with Mobile Devices and Services (Oldenburg, Germany) (MobileHCI ’20). Association for Computing Machinery, New York, NY, USA, Article 9, 4 pages. https://doi.org/10.1145/3406324.3410710

[25] Toby Jia-Jun Li, Lindsay Popowski, Tom Mitchell, and Brad A. Myers. 2021. ScreenVec: Semantic Embedding of GUI Screens and GUI Components. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445049

[26] Yang Li, Jiacong He, Xin Zhou, Yuan Zhang, and Jason Baldridge. 2020. Map- ping Model Predictions. In Proceedings of the 33rd ACM Conference on Human Factors in Computing Systems (CHI ‘20). Association for Computing Machinery, New York, NY, USA, 3445538.

[27] Chunggi Lee, Sanghoon Kim, Dongyun Han, Hongjun Yang, Young-Woo Park, Bum Chul Kwon, and Sungahn Ko. 2020. GUComp: A GUI Design Assistant with Real-Time, Multi-Faceted Feedback. Association for Computing Machinery, New York, NY, USA, Article 9, 4 pages. https://doi.org/10.1145/3406324.3410710

[28] Zachary C. Lipton. 2017. The Mythos of Model Interpretability. arXiv:1606.03490 [cs,LG]

[29] Hoo Loranger. 2015. Beyond Blue Links: Making Clickable Elements Recognizable. Nielsen Norman Group. https://www.nngroup.com/articles/clickable-elements/

[30] Scott M. Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In Proceedings of the 31st International Conference on Neural Information Processing Systems (Long Beach, California, USA) (NIPS ’17). Curran Associates Inc., Red Hook, NY, USA, 4768–4777.

[31] Nicolas Papernot and Patrick D. McDaniel. 2018. Deep k-Nearest Neighbors: Towards Confident, Interpretable and Robust Deep Learning. CoRR abs/1803.04765 (2018). arXiv:1803.04765 http://arxiv.org/abs/1803.04765

[32] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. “Why Should I Trust You?” Explaining the Predictions of Any Classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (San Francisco, California, USA) (KDD ’16). Association for Computing Machinery, New York, NY, USA, 1135–1144. https://doi.org/10.1145/2939672.2939778

[33] Eldon Schoop, Forrest Huang, and Bjorn Hartmann. 2021. UMLAUT: Debugging Deep Learning Programs Using Program Structure and Model Behavior. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445538

[34] Jessica Schrouff, Sebastien Baur, Shaobo Hou, Diana Mincu, Eric Loreaux, Ralph Blanes, James Wexler, Alan Karthikesalingam, and Been Kim. 2021. Best of both worlds: local and global explanations with human-understandable concepts. CoRR abs/2106.08641 (2021). arXiv:2106.08641 https://arxiv.org/abs/2106.08641

[35] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedan- tam, Devi Parikh, and Dhruv Batra. 2017. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In 2017 IEEE International Con- ference on Computer Vision (ICCV). 618–626. https://doi.org/10.1109/ICCV.2017.74

[36] Mukund Sundararajan, Ankur Taly, and Qiqi Yan. 2017. Axiomatic Attribution for Deep Networks. In Proceedings of the 34th International Conference on Machine Learning - Volume 70 (Sydney, NSW, Australia) (ICML’17). JMLR.org, 3319–3328.

[37] Amanda Swearngin and Yang Li. 2019. Modeling Mobile Interface Tappability Using Crowdsourcing and Deep Learning. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. ACM, Glasgow Scotland Uk, 1–11. https://doi.org/10.1145/3290605.3300305

[38] Amanda Swearngin, Chenglong Wang, Alannah Oleson, James Fogarty, and Amy J. Ko. 2020. Scout: Rapid Exploration of Interface Layout Alternatives through High-Level Design Constraints. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376597

[39] Robert Stuart Weiss. 1994. Learning from strangers: The art and method of quali- tative interview studies. Free Press. ix, 246 pages.

[40] Gerhard Widmer and Mirolrub Koubat. 1996. Learning in the Presence of Concept Drift and Hidden Contexts. Mach. Learn. 23, 1 (April 1996), 69–101. https://
A USER STUDY FIGURES
Following are the UIs and outputs of our explanation algorithms shown to participants in the user evaluation in section 7.
A.1 Example 1: Onboarding Example

Input Image and Region

Model tap prob: 99.15%

Most similar examples
(tappable on left, non-tappable on right)

Saliency Heatmap

Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image
A.2 Example 2

Input Image and Region
Model tap prob: 5.94%

Know on the go
While you're on the go, enjoy free access to great places to eat and things to do nearby... wherever you are.

Saliency Heatmap
Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image

Most similar examples
(tappable on left, non-tappable on right)
A.3 Example 3

Input Image and Region

Model tap prob: 8.22%

1 large, 1 small

Saliency Heatmap

Left: Input image and region 
Middle: Heatmap 
Right: Heatmap * Image

Most similar examples
(tappable on left, non-tappable on right)

Sign Out

Flight Search

Cholesterol 204.4mg

Food Instructions
A.4 Example 4

Input Image and Region

Model tap prob: 53.42%

Most similar examples (tappable on left, non-tappable on right)

Saliency Heatmap

Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image
A.5 Example 5

Input Image and Region

Model tap prob: 90.37%

CONNECT TO SOUNDS SYSTEM

On your nearest Sonos player, press and release the button as shown below.

→ BACK

Most similar examples
(tappable on left, non-tappable on right)

Saliency Heatmap

Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image

Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image

TAGS:

JioChat

Resend SMS

MyFRITZ!

diastol
A.6 Example 6

Input Image and Region
Model tap prob: 48.65%

Most similar examples
(tappable on left, non-tappable on right)

Saliency Heatmap
Left: Input image and region
Middle: Heatmap
Right: Heatmap * Image