HARPT: A Corpus for Analyzing Consumers' Trust and Privacy Concerns in Mobile Health Apps

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ABSTRACT

We present HARPT, a large-scale annotated corpus of mobile health app store reviews aimed at advancing research in user privacy and trust. The dataset comprises over 480,000 user reviews labeled into seven categories that capture critical aspects of trust in applications, trust in providers and privacy concerns. Creating HARPT required addressing multiple complexities, such as defining a nuanced label schema, isolating relevant content from large volumes of noisy data, and designing an annotation strategy that balanced scalability with accuracy. This strategy integrated rule-based filtering, iterative manual labeling with review, targeted data augmentation, and weak supervision using transformer-based classifiers to accelerate coverage. In parallel, a carefully curated subset of 7,000 reviews was manually annotated to support model development and evaluation. We benchmark a broad range of classification models, demonstrating that strong performance is achievable and providing a baseline for future research. HARPT is released as a public resource to support work in health informatics, cybersecurity, and natural language processing.

KEYWORDS

mobile health apps, user reviews, trust and privacy, weak supervision, text classification

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1 INTRODUCTION

Mobile health (mHealth) applications (apps) play a growing role in healthcare delivery, enabling patients to schedule appointments, view medical records, engage in telemedicine, and manage chronic

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conditions directly from their smartphones. As these platforms collect and process increasingly sensitive personal health information, questions surrounding privacy, trust, and data governance have become central to patient adoption and ongoing usage [25] [11] [12]. Despite the growing prevalence of mHealth apps, few largescale, publicly available datasets exist that capture real-world user perspectives regarding privacy concerns and trust-related factors in these digital platforms.

To address this gap, we introduce $\underline{\mathbf{H}}$ ealth $\underline{\mathbf{A}}$ pp $\underline{\mathbf{R}}$ eviews for $\underline{\mathbf{P}}$ rivacy and $\underline{\mathbf{T}}$ rust (HARPT), a large-scale labeled dataset derived from over 480,000 user reviews of both patient portal and telehealth applications. HARPT uniquely focuses on classifying reviews according to privacy concerns and multiple dimensions of trust, including trust in the healthcare provider and trust in the application itself. The dataset was developed using a multi-stage process that combined targeted keyword filtering, multi-rater manual annotation, data augmentation, and weak supervision leveraging transformer-based models.

In addition to releasing the HARPT dataset, we also benchmark its utility for supervised text classification. We evaluate a variety of traditional machine learning classifiers as well as multiple transformer models, providing strong baselines for future research in privacy and trust detection, healthcare app user experience, and sentiment analysis. By releasing both the labeled dataset and its corresponding benchmark results, HARPT aims to support ongoing research into privacy-preserving healthcare technologies, trust modeling, and patient-centered digital health innovation.

2 RELATED WORK

Privacy and security concerns within mHealth apps and digital health IoT systems has been explored in prior literature both conceptually and technically. Some studies have proposed frameworks for managing privacy risks in healthcare IoT ecosystems [6] [13], or the use of fuzzy linguistic models to quantify trust in eHealth services [28]. Broader systematic reviews have synthesized user attitudes toward health data sharing more generally [3], and privacy issues in mobile apps specifically in developing countries have been reviewed by Diallo et al. [9]. Many of these studies, while valuable, primarily use survey-based, mixed-method, or theoretical approaches without releasing public datasets.

A smaller but growing body of work has attempted to extract privacy and trust signals directly from user-generated content such as app reviews. Mukherjee et al. [26] conducted a large-scale empirical analysis of over two million mobile app reviews to identify

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security and privacy concerns. Nema et al. [27] examined user perspectives on app privacy at scale across app marketplaces. Zhang et al. [37] applied topic modeling techniques to automatically extract privacy concern topics from app reviews. Ebrahimi and Mahmoud [10] developed unsupervised summarization approaches to identify privacy concerns in reviews, while Sorathiya and Ginde [32] designed hybrid models to mine ethical concerns from app reviews. Hatamian et al. [16] used semi-supervised mining to analyze privacy perceptions of smartphone users in app stores. Finally, Sabrina and Weng [29] explored misinformation classification methods for mHealth app reviews, while Saheb et al. [30] examined privacy aspects in COVID contact tracing apps.

Although these works demonstrate growing interest in extracting privacy and trust signals from app reviews, many rely on proprietary or limited datasets, focus on non-health domains, or do not publicly release annotated datasets for reproducible research. Furthermore, much of the existing research focuses on general mobile apps, whereas mobile health applications pose unique privacy challenges due to the sensitivity of health-related user data. Importantly, prior studies typically address isolated aspects of trust or privacy without jointly examining privacy concerns, trust in applications, and trust in providers. HARPT addresses this gap by capturing these dimensions in a unified, labeled dataset.

Our work builds upon the literature by introducing a large-scale, publicly available dataset of 480,450 mobile health app reviews weakly labeled for trust and privacy indicators. Using a combination of manual annotation, data augmentation and weak supervision, we create a new resource that directly supports future research on privacy and trust in mHealth app store reviews.

3 DATASET CONSTRUCTION

3.1 Initial Data Collection

We first collected an initial dataset of approximately 457,165 user reviews from the Google Play Store. The reviews were scraped from mobile health applications covering both patient portal and telehealth services. To improve the relevance of candidate reviews for manual annotation, we applied a keyword-based filtering process. We curated a list of representative keywords for each of the target classes. Reviews containing at least one of these keywords were retained for further annotation. This filtering step reduced the size of the candidate pool while ensuring adequate representation of the target concepts.

3.2 Annotation

From the filtered pool, a random sample of 4,000 reviews was selected for manual annotation. The reviews were annotated into one of seven mutually exclusive classes: competence, reliability, support, risk, ethicality, data quality, and data control. The annotation process followed a three-pass review protocol. First, an initial annotator labeled a batch of 1,000 reviews. Next, two independent reviewers reviewed each batch and either confirmed or suggested an alternative label. The final label was determined via majority vote across the three annotators. In cases where all three annotators disagreed (which occurred only once), the lead researcher adjudicated and assigned the final label. This multi-pass process

Table 1: HARPT categories with descriptions and representative review excerpts.

Label	Description + Example
Data Control	Concerns about consent, third-party access, or control over per- sonal data. "It's great the app lets me review and delete my medical records whenever I want."
Data Quality	Issues with incorrect, outdated, or incomplete health data. "The app is showing someone else's health record!"
Reliability	App crashes, login failures, or inconsistent functionality. "I can't login! Every time I enter my username and password it just loads and loads."
Support	User experience with help services or communication. "Customer support responded to my query within a few hours and helped me resolve my issue."
Risk	Worries about security, breaches, or misuse of data. "I'm worried about how the app stores my personal health records."
Competence	Perceptions of provider professionalism and care quality. "I re- ceived tailored advice based on my health data and it helped me manage my condition better."
Ethicality	Judgments of provider fairness, transparency, or responsibility. "I love that the app asks for my consent before collecting my data."

ensured high-quality annotations and minimized label noise. Interrater agreement was quantified using **Fleiss' Kappa** [14], yielding a value of **0.877**, which indicates almost perfect agreement among annotators.

3.3 Theoretical Framework for Privacy and Trust

The annotation schema for this dataset is grounded in established theories of privacy and trust as applied to healthcare technologies. We organize the labels under three overarching constructs: *Privacy Concerns, Trust in Application,* and *Trust in Provider*.

For *Privacy Concerns*, the dimensions were informed by prior work in privacy concern frameworks like Internet Users' Information Privacy Concerns (IUIPC) model [21], which conceptualizes privacy concerns as a second-order construct encompassing data collection, user control, and awareness of privacy practices. Others such as the perceived control in ubiquitous computing [33], and healthcare-specific trust models [8] [35] [34] align with common issues faced in mHealth applications, where users interact with sensitive personal health data, exercise limited control over information sharing, and often lack transparency about data usage. These privacy constructs reflect concerns related to personal health information sharing, data control, consent, and information quality, consistent with prior frameworks in both healthcare and ubiquitous computing. Our annotation schema operationalizes these concerns through the *data control* and *data quality* labels.

For *Trust in Provider*, we build on organizational trust frameworks, particularly the integrative model proposed by Mayer et al. [22], ethical perspectives articulated by Hosmer [18], and trust scales developed by McKnight et al. [24]. These models emphasize provider competence, ethicality, integrity, and benevolence as critical antecedents to trust formation, which directly map to our *competence* and *ethicality* labels.

For *Trust in Application*, we incorporate perspectives from the Trust in Technology literature [23], e-commerce trust models [15], and technology acceptance frameworks considering both trust and





privacy concerns [8]. In mHealth applications, users' trust in the technical system is shaped by perceived reliability, security, technical support, and vulnerability to risks. These factors are reflected in our schema through the *reliability*, *support*, and *risk* categories.

Collectively, these theoretical foundations ensure that our annotation schema captures both the privacy and trust dimensions most relevant to users' perceptions of healthcare applications, where users interact simultaneously with both healthcare providers and complex digital platforms mediating highly sensitive personal data.

3.4 Annotation Schema and Label Definitions

Each review was assigned to one of seven mutually exclusive categories corresponding to the trust and privacy constructs (See Table 1).

3.5 Data Augmentation and Balancing

The manually labeled dataset exhibited class imbalance, with certain categories (e.g., competence) being overrepresented. To address this imbalance, we applied data augmentation using back-translation via French, Spanish, and German. The minority classes were oversampled through augmentation, while the majority class was downsampled to 1,000 instances. The final balanced training set contained 7,000 reviews. To assess semantic fidelity of the back-translated text, we computed the **BLEU score** between the original and back-translated reviews. This yielded a score of **30.43** which indicates moderate lexical overlap and preservation of core meaning.

3.6 Model Evaluation on Ground Truth Dataset

We trained and evaluated a set of machine learning and transformerbased models on the 7,000-instance balanced dataset. The traditional models included Support Vector Machines (SVM) [7], Random Forest [2], Logistic Regression [17], XGBoost [4], and LightGBM [19]. The transformer-based models included DistilBERT [31], ELECTRA [5], XLNet [36], and RoBERTa [20]. These experiments (see Figure 2) allowed us to assess classification performance across model architectures and informed model selection for weak supervision.

3.7 Large-Scale Dataset Collection

Following the ground truth evaluation, we conducted a second, larger data collection process, scraping 480,450 user reviews across 67 mobile health apps. This larger dataset also included both patient portal and telehealth applications. Based on the model evaluation results, we selected XLNet as the best-performing model for weak supervision. The trained XLNet model was applied to classify each review into one of the seven target classes. The resulting weakly labeled dataset constitutes the primary dataset release described in this paper.

Tabl	le 2:	Dataset	Summary	Statistics
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Statistic	Value		
Total Reviews Time Range Unique Apps App Types Top 3 Apps	480,450 2011–2025 67 64.8% Patient Portal, 35.2% Telehealth MyChart (19.4%), FollowMyHealth (14.7%), healow (9.8%)		
Mean Word Count Median Word Count	16.49 10		
Star Ratings	5 stars: 65.4%, 4 stars: 9.6%, 3 stars: 4.3%, 2 stars: 4.0%, 1 star: 16.7%		
Sentiment Labels	competence: 44.3%, reliability: 27.5%, data control: 13.5%, data quality: 9.7%, support: 2.2%, risk: 1.4%, ethicality: 1.3%		

4 DATASET OVERVIEW

4.1 Descriptive Statistics

The final HARPT dataset contains 480,450 unique user reviews collected across 67 mobile health applications between 2011 and 2025. After removing duplicates and user identifiers, we produced the final cleaned dataset used for benchmarking. Reviews in the dataset have an average word count of 16.5 words (SD = 19.46), with a maximum review length of 675 words. The majority of reviews contain between 4 and 21 words, reflecting the brief nature of typical app store feedback. Star ratings are skewed toward positive sentiment, with 65.4% of reviews receiving 5 stars and 16.7% receiving 1 star.

The reviews span a wide time range, with data collected from July 2011 through April 2025, allowing longitudinal analyses of trust and privacy issues over time.

4.2 Sentiment Label Distribution

The seven annotated labels are distributed as follows: Competence (212,950 reviews), Reliability (132,149), Data Control (64,962), Data Quality (46,544), Support (10,745), Risk (7,016), and Ethicality (6,084). The most frequent categories reflect users' concerns with provider competence and application reliability.

4.3 Applications

The most commonly reviewed apps are MyChart (19.4% of reviews), FollowMyHealth (14.7%), Healow (9.8%), Practo (9.1%), and Doctor on Demand (7.3%), together representing over 60% of the dataset.

Model Performance Before and After Back Translation Augmentation 90 Original Augmented 86.00 86.00 85.52 85.37 85 84.36 82.29 82.15 80.97 Weighted F1-Score (%) 80 75 72.90 71.73 71.42 69.44 69.32 70 67.89 67.55 66.71 65 63.70 Logistic Regression DistiBERT 60 LightGBM +LINet ELECTRA ROBERTS Forest SUM +680051

Figure 2: Model performance (weighted F1-score) before and after back-translation augmentation across various classifiers.

The dataset covers both patient portal apps and telehealth platforms. Approximately 65% of reviews come from patient portal apps and 35% from telehealth apps.

4.4 Dataset Release

The HARPT dataset, including 480,450 weakly labeled reviews and the 7,000 ground truth subset, is publicly available on Dataverse (https://doi.org/10.7910/DVN/U6OF6F). The fine-tuned XLNet model trained on this data is available via Hugging Face

(https://huggingface.co/tk648/XLNet-base-finetuned-HARPT). Both resources are released under *Creative Commons 4.0* to support reproducible research.

5 EXPERIMENTS

To provide baseline performance on the HARPT dataset, we trained and evaluated both classical machine learning models and state-ofthe-art transformer-based models.

For the classical models, we implemented a Random Forest classifier using TF-IDF vectorized features extracted from the text reviews. Hyperparameters including number of estimators, maximum depth, and minimum samples per split were tuned via grid search.

For the transformer-based models, we fine-tuned both Distil-BERT and RoBERTa on the annotated training data. Fine-tuning was performed using mixed precision training with GPUs, utilizing early stopping and learning rate schedulers to optimize convergence. All hyperparameters were tuned using the sweeps feature on the Weights and Biases platform [1].

5.1 Results

The HARPT dataset includes the seven classes: *data control, data quality, risk, support, reliability, competence,* and *ethicality.*

These results demonstrate that both classical and transformerbased models achieve strong performance.

Table 3: Benchmark performance on the HARPT dataset

Model	Accuracy	F1	Precision	Recall
Random Forest	94.00%	93.96%	94.05%	94.00%
DistilBERT	91.25%	91.27%	91.32%	91.25%
RoBERTa	89.02%	89.04%	89.13%	89.02%

6 CONCLUSION

In this paper, we present HARPT, a novel labeled dataset of user reviews from mobile health applications focused on trust and privacy concerns. Through a combination of manual annotation, weak supervision, and review scraping, we generate a publicly available resource consisting of 480,450 reviews labeled across seven privacy and trust-related categories. We also benchmark multiple classification models, providing initial baselines for future work. We make both the manual annotated ground truth and large-scale weakly supervised dataset publicly available to facilitate further research on privacy and trust in mobile apps.

7 ETHICS STATEMENT

This dataset was collected from publicly available user reviews on Google Play, containing no private or protected health information. Usernames were anonymized during preprocessing. Annotations were conducted by trained annotators under multiple review stages. The dataset is released solely for research purposes, with the expectation that all use will respect user privacy and ethical research standards.

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