Abstract

In December of 2020, Apple started to require app developers to self-report privacy label annotations on their apps indicating what data is collected and how it is used. To understand the adoption and shifts in privacy labels in the App Store, we collected nearly weekly snapshots of over 1.6 million apps for over a year (July 15, 2021 – October 25, 2022) to understand the dynamics of privacy label ecosystem. Nearly two years after privacy labels launched, only 70.1% of apps have privacy labels, but we observed an increase of 28% during the measurement period. Privacy label adoption rates are mostly driven by new apps rather than older apps coming into compliance. Of apps with labels, 18.1% collect data used to track users, 38.1% collect data that is linked to a user identity, and 42.0% collect data that is not linked. A surprisingly large share (41.8%) of apps with labels indicate that they do not collect any data, and while we do not perform direct analysis of the apps to verify this claim, we observe that it is likely that many of these apps are choosing a Data Not Collected label due to being forced to select a label, rather than this being the true behavior of the app. Moreover, for apps that have assigned labels during the measurement period nearly all do not change their labels, and when they do, the new labels indicate more data collection than less. This suggests that privacy labels may be a “set once” mechanism for developers that may not actually provide users with the clarity needed to make informed privacy decisions.

1 Introduction

Ubiquitous data collection embedded within modern web and mobile ecosystems has led to several interventions meant to empower users in managing their privacy. Notably, privacy policies offer free-text explanations of data collection and use but are often complicated and difficult for users to comprehend and apply to decision making [1, 2]. Privacy nutrition labels (or privacy labels) [3] offer an alternative approach that is modeled after food nutrition labeling [4], where a privacy nutrition label compactly describes the data collection and usage practices of a service via prescribed fields [5, 3, 6].

In December of 2020, Apple mandated developers to self-report privacy labels for new and version-updated apps. Apple’s privacy labels (see Figure 1 and Figure 2) standardizes information such as the type of data collected by an app (e.g., Email Address, Payment Info, Precise Location), the purpose of the collection (e.g., App Functionality, Product Personalization), and privacy-relevant aspects associated with the data collection (e.g., tracking users across apps and websites, linking to user identities, de-identifying or anonymization). In April of 2022, Google followed and announced its own form of privacy nutrition labels, data safety labels, for apps on the Play Store [7].

We conducted more than a year-long (July 15, 2021 – October 25, 2022) longitudinal analysis of over 1.6 million apps in the iOS App Stores adoption to understand how developers are selecting and changing privacy labels. Importantly, we focus only on the adoption and dynamics of the privacy labels ecosystem, rather than verifying their accuracy. We seek to answer the following research questions: (RQ1) What are the trends of privacy labels adoption? (RQ2) What factors affect the adoption of privacy labels and how do they change? (RQ3) How are different dimensions of apps (based on app metadata) selecting privacy labels?

In answering RQ1, in October 2022, nearly two years after Apple’s new policy, 70.1% \((n = 1,110,448)\) of apps have a privacy label, a 28% increase since the start of the measurement period (670,547 vs. 1,110,448). However, this increase
was primarily driven by new apps added to the store that are required to have a label rather than older, legacy apps being updated or voluntarily adding labels.

When considering RQ2 and how labels change, it is again important to note that privacy labels are self-reported, entirely at the discretion of the developer, and not validated by Apple. As such, we observed different labeling depending whether the developers were forced to add labels, like a new or updated app, as compared to voluntarily adding labels. Fifty percent of developers forced to add labels when releasing a version update opted for Data Not Collected but only forty-one percent did so when voluntarily adding labels. Many developers may see privacy labels as an obstacle to the ultimate goal of adding an app to the store, rather than a mechanism to communicate about privacy practices. Moreover, we observed very few shifts in privacy labels (only 18,698 apps of more than 1M apps with labels). When labels do change, they tend to report more data collection.

Finally, we divided the apps based on a number of criteria in answering RQ3, including their (age-based) content rating, cost, popularity, and app-size. For example, when considering content-rating, 16% and 52% of apps with a content rating of 4+ and 9+, respectively, indicate that they collect data targeting users which can include children and would be subject to data collection and tracking standards in line with Children’s Online Privacy Protection Act (COPPA). When comparing paid vs. free apps, more free apps use privacy labels that indicate data collection and tracking, perhaps reflecting additional revenue streams from free apps in targeted advertising and/or selling user data.

Our findings suggest that there are a number of factors in how developers select and update privacy labels in the Apple App Store. As labels are not validated, the true practices may vary significantly from what is reported, especially for apps that explicitly report that they do not collect any data. Our measurement offers important baselines for future work in app analysis. Comprehensive and continual transparent measurements at scale provide important context accountability for developers. The trends and practices we present in our study offer important perspective into a particularly pressing issue regarding the adoption and use of declared data collection practices on the App Store, especially as privacy nutrition labels are becoming the de facto standards across the mobile app marketplaces beyond just Apple.

2 Related Work

Researchers have gathered evidence of online services data collection behaviors via longitudinal measurements across various platforms [8, 9, 10, 11, 12, 13, 14, 15]. Analysis of mobile apps showed sensitive data, including PII [14], is collected and shared with third parties without user consent [12, 16]. Data collection practices were prevalent across measurements of apps in different geographic regions [17], categories [18, 19], price brackets [13, 20, 21], and app markets [22, 23, 24].

Both Android and iOS require all applications to use install and/or runtime permissions [25, 26], different from privacy labels. Prior research showed low attention and comprehension for install-time permissions [27]. Felt et al. [28] further found evidence over-permissioning [28]. Reardon et al. [29] showed apps circumventing the permissions by gaining access to data using covert and side channels.

Kelly et al. [3, 30] developed a privacy label to describe how websites collect, use, and share users’ personal information, and later extended [6] in the design of “Privacy Facts.” Subsequently, Emami-Naeini et al. [31, 5] developed and evaluated similar labels for Internet of Things (IoT) devices and found that users factor privacy risk perceptions into their purchase. Over the years, multiple researchers have studied and provided recommendations on designing similar privacy notices from a variety of perspectives. [32, 33, 34, 30, 6, 31, 5, 35].

In related work on Apples privacy labels, Li et al. [36] interviewed 12 developers about selecting labels. Many developers misunderstood the process, leading to both under-reporting and over-reporting data collection. Kollnig et al. [37] evaluated 1,759 apps before and after they added a privacy label. They looked at instances of apps collecting an identifier for cross-device tracking, and inferred the impact that privacy labels had on such collection. They found apps adopting measures to circumvent Apple’s detection of their tracking activity. Zhang et al. [38] recently investigated the usability of Apple’s Privacy Labels using semi-structured interviews with 24 iOS users. This study surfaced several potential concerns with the current implementation of privacy labels including clarity of the terse explanations provided by Apple for each label’s meaning, and the lack of awareness that the labels are even included in the App Store listings.

Garg et al. [39] discovered that privacy label disclosures of sensitive information reduce app demand. Gardner et al. [40] developed a tool to assist developers to prompt them of possible functionality that would require a privacy label. Xiao et al. [41] analyzed 5,102 apps by checking the privacy labels against actual data flows, discovering that 67% of those apps failed to accurately disclose their data collection practices, particularly around the use of User ID, Device ID, and Location data. Scoccia et al. [42] analyzed a small subset ($n = 17,312$) of apps on the App Store. They captured two snapshots of the subset of apps, seven months apart. They observed a decrease in the number of apps that collect data for tracking purposes, but an increase in overall data collection. Among our various additional results, we confirm their
findings using 50 snapshots of 1.6M apps.

Most relevant to our work is analysis by Li et al. [43]. They collected weekly snapshots of privacy labels on the store between April 2 and November 5, 2021. They reported that only 2.7% of apps during their collection period voluntarily added a privacy label, suggesting that inactive apps have little incentive to create privacy labels. They also observed 137,088 apps that created their first label in April 2021, and found that developers of these apps rarely updated privacy labels after creating one. We observed over 1M apps with labels that adopted a label at any point in our 66-week collection period before we could confidently corroborate their findings. Our analysis both verifies and significantly surpasses the work of Li et al., whose 31 weeks of analysis overlaps with less than half of our 66-week collection period. We offer a detailed analysis, and consider all criteria included in the privacy labels for each app, which they did not collect. We report not just on high-level privacy label data from an app’s install page (see the boxes indicating Privacy Types on the left of Figure 2) but also include all privacy details about how data is used, i.e., Purpose, and the granularity of the data collected, i.e., Data Types (see right of Figure 2). We evaluate each label in a complete and comprehensive manner. We also report on a deeper set of app metadata to understand correlations with content rating, user rating counts, release dates, app size, and app price.

3 Apple’s Privacy Labels

In December 2020, Apple adopted app-based privacy labels, making them mandatory for all new and updated apps on the App Store [44], and Google introduced data safety labels for the Play Store in April 2022 [7]. Here, we focus exclusively on Apple’s privacy label, which are similar in style to “Privacy Facts” by Kelly et al [6]. The structure of Apple’s privacy labels is hierarchical (see Figure 2 for details) and are the combination of four sections of information. In the top level (to the left in the diagram) of the label hierarchy are four distinct Privacy Types, three of which describe ways of using data. An app’s privacy label may contain a combination of one, two, or all three of these Privacy Types. The fourth Privacy Type, entitled Data Not Collected, is displayed with an image of a blue checkbox and indicates that the developer does not collect any data from this app. Data Not Collected is mutually exclusive with the other three Privacy Types (see Figure 4). When an app adds a label with the Data Not Collected Privacy Type, it states that it does not collect any data from the user, and therefore does not include other Privacy Types or any Purposes, Data Categories, or Data Types.

Among the three data collection Privacy Types, the first, Data Used to Track You, indicates that data collected may be used to track users across apps and websites owned by other companies, including sharing data with third-party advertising networks and data brokers. The second, Data Linked to You, indicates that data is collected and is linked to the user’s identity. The third, Data Not Linked to You, indicates that data is collected but is de-identified or anonymized and is therefore not linked to the user’s identity.

The next level down in the label hierarchy are the Purposes, which are categories of data collection, such as Contact Info, Location, and Purchases. It is unlikely for an app to be labeled so, but it is possible for all 14 Data Categories to be listed under each of the three Privacy Types. And finally, at the bottom level (to the right in the diagram) are the Data Types, which provide the most detailed grouping of the data collected into 32 descriptive types, such as Coarse Location, Precise Location, Gameplay Content, or Emails or Text Messages.

Figure 1 (left) provides an example of a privacy label as displayed. Each box reports the Privacy Type, a short description of that type, and then within the box, each of the Data Categories. When one clicks on a given category, a popup screen is displayed, see Figure 1 (right) with details about the Purposes and specific Data Types.

4 Data Collection Methods

Beginning in July 15, 2022, each week we collect, store, and analyze data for an average of 1,598,134 (SD = 11, 192) apps. We enumerate all app URLs found on the Apple App Store (using the App Store’s own site-map) and parse the privacy labels and metadata for each app. When parsing the data we extract: (i) app properties such as: (a) cost, (b) size, (c) developer, (d) content rating, (e) release date, (f) and genre, (ii) what data is collected, (iii) what is the purpose of the collection, (iv) and how the data will be used. The process proceeds in two stages: first, capturing the addition or removal of apps from the App Store; and second, creating a new snapshot for retrieving the associated app metadata and privacy label information.

First, a cron job will retrieve and parse the site-map from https://apps.apple.com weekly to extract individual app
Figure 1: (left) An illustrative example of a privacy label from the Apple App Store, and (right) an illustrative example of the privacy label details from the Apple App Store. The details display the Purposes for the data collection and the detailed information about the Data Types collected.

Figure 2: A privacy label consists of four hierarchical levels of information. The Privacy Type broadly identifies how the data collected will be used. The Purpose provides more detail on how each data type is used. The Data Category is a categorization the Data Type which is a detailed description of the type of data collected.

Figure 3: A longitudinal view over the year-long collection period of the total number of apps and the total number of apps with privacy labels (compliant apps). For comparison, we also display the four Privacy Types over the same period. Each data point represents a snapshot of the Apple App Store on that date.

URLs, which are then insert the URLs into a database table for use in retrieving the privacy label information and associated app metadata. Second, using the full list of app URLs, a second process retrieves the app privacy labels and metadata. This is accomplished by parsing a JSON string embedded within each apps app-store page. The privacy label are parsed directly from the HTML, which includes both the Privacy Types and Data Categories. To get the extended privacy label details, i.e., Purposes and Data Types, we perform a GET request to the Apple catalog API at https://amp-api.apps.apple.com/v1/catalog/.

The resulting dataset contains a total of 2,005,552 unique apps, with roughly 1.6M active per week. We had some data collection interruptions in late April through early September 2022 were our crawler was taking longer than a week to complete or was unable to get a full craw of the App Store. When this occurred we excluded this run. In total, we have 50 weeks of data during the 66 week data collection period.
5 Limitations and Ethical Considerations

We sought to collect our data in an ethical manner by only accessing public data on the Apple App Store web pages. We do not abuse any protocols or hidden APIs, but our measurement requests do incur an additional burden on Apple’s servers. To alleviate that burden we place limits on the GET requests. We request the web pages containing the app metadata in batches containing only 100 apps and initiate a sleep time of 10 seconds between batches. We additionally deploy an exponential backoff for errors to further reduce over requesting Apple’s servers. At times, this led us to not being able to complete a crawl within a week. When this occurred, this data was excluded, and as such we are limited in what we can claim about weekly changes and instead report on changes between snapshots.

Privacy labels are self-reported and selected by developers. They are neither regulated by Apple nor vetted by us. These values may not accurately reflect actual data collection practices in the wild. However, we do provide examples where we believe labels are inaccurate (subsection 7.3) based on circumstantial evidence. We cannot report on inaccuracies at scale, though, given the nature of our measurement, but we do discuss possible methods to perform accuracy checks in section 9. While we agree that an analysis of the accuracy of privacy labels is interesting, we argue that this is beyond the scope of the analysis of this longitudinal measurement.

Privacy labels were made mandatory on the App Store in December 2020. Since our collection of labels began in July 2021, we do not report on label adoption prior to that date. However, since less than half of the apps on the App Store had adopted privacy labels when we began our study, our year-long analysis importantly captured the adoption and changes of privacy labels from both, old and new apps.

The numbers presented below offer interesting insight into how apps posture their privacy and data collection practices to users, especially in the absence of any regulation from the App Store. They show us how apps wish to be perceived, and if they are incentivized to adopt and change these labels based on what users can see before choosing to install an app, regardless of the accuracy of the stated information.

6 RQ1: Overall App Store Trends

In addressing RQ1, we consider each crawl of the app store and how many apps have labels and of what kinds (see Figure 3). There are an average 1,588,758 (SD = 22,879) total apps in each crawl, and on average 10,989 (SD = 11,063) newly published and 44,043 (SD = 20,031) removed apps in each crawl. At the end of the data collection period, 70.1% (n = 1,110,448) of apps had a privacy label, which is a 28% increase from the start where only 42.1% (n = 670,547) had labels. There still remains 39.5% (n = 621,908) of apps without privacy labels.

We find that 32.9% (n = 365,295) of apps have more than one Privacy Type (see Figure 4), and 7.1% (n = 78,606) of apps have all three Privacy Types. The most common (n = 242,698, 21.9%) combination of Privacy Types is the Data Linked to You together with Data Not Linked to You, and Data Not Linked to You is the most common Privacy Type.
Type overall with 42.0% \( (n = 466,057) \), followed closely by Data Not Collected (41.8%, \( n = 463,720 \)) of apps with labels. Note that Data Not Collected is mutually exclusive with the other Privacy Type, and an app reporting Data Not Collected cannot report other privacy behavior.

The reported prescribed Purposes for the privacy labels are only provided for the Data Linked to You and Data Not Linked to You Privacy Types, as the purpose for the Data Used to Track You is by definition only for targeted advertising. Figure 5 shows the ratios of the six Purposes. The denominator for the ratios in this figure is the total number of apps labeled with the specific Privacy Type. In the final snapshot of collection (October 25, 2022), the most common Purposes for collecting data linked to users’ identities are App Functionality \((n = 370,069; 71.0\%)\) and Analytics \((n = 194,962; 46.1\%)\), and for collecting data not linked are App Functionality \((n = 330,721; 71.0\%)\) and Analytics \((n = 277,449; 43.1\%)\). These ratios of Purpose were shown to be stable over the study period.

When we review the Data Categories contained under each Purpose, we find differences in the most common categories of data collection between Data Linked to You and Data Not Linked to You. For example, under Data Linked to You for the Purpose of App Functionality, Contact Info \((n = 292,137; 69.1\%)\) is the most common Data Category, but under Data Not Linked to You for the same Purpose of App Functionality it is Diagnostics \((n = 192,007; 41.2\%)\). This suggests that while App Functionality is often given as the reason for data collection, the category of data collected depends on whether that data is linked or not linked to a user’s identity. A summary of the ratios of Data Categories by Purpose can be found in the heatmap of Figure 6.

Figure 7 shows the ratios of the 14 Data Categories for each of the three Privacy Types as a heatmap. The most common Data Categories found under Data Used to Track You are Identifiers \((n = 136,412; 67.7\%)\) and Usage Data \((n = 117,246, 58.2\%)\). The Identifiers category contains the User ID and Device ID Data Types, which are frequently used to track users for the placement of targeted advertisements. The most common Data Categories under Data Linked to You are Contact Info \((n = 307,403; 72.7\%)\) and again Identifiers \((n = 274,063; 64.8\%)\). Very few apps report collecting and linked very sensitive user data such as Health & Fitness \((n = 18,683, 4.4\%)\) and Sensitive Info \((n = 13,594, 3.2\%)\).

Apps have 2.2 \((SD = 1.5)\) Data Categories listed under
Data Used to Track You, 6.1 (SD = 6.2) under Data Linked to You, and 3.6 (SD = 3.5) under Data Not Linked to You, on average. Viewed another way, there were a total of 4,692,465 instances of collected Data Categories on the app store, and 9.5% (n = 444,875) of them are Data Used to Track You, 54.6% (n = 2,560,243) are Data Linked to You, and 36.0% (n = 1,687,347) are Data Not Linked to You. A majority of data collected on the App Store is linked to users' identities and not anonymously collected.

Finally, at the most detailed level are the Data Types. The specific detail about the type of data collected is important for broadly defined Data Categories like Contact Info and User Content. For example, the Contact Info category may include the Physical Address, Email Address, Name, and Phone Number Data Types. For Data Used to Track You the most common Data Types collected are the Device ID (n = 116,500, 57.8%) followed by Advertising Data (n = 86,223, 42.8%) and Product Interactions (n = 73,265, 36.4%). For Data Linked to You the most common are Email Address (n = 250,255, 59.2%), Name (n = 255,148, 60.3%), User ID (n = 220,790, 52.2%), and Phone Number (n = 209,272, 49.5%). Refer to Figure 8 for full results.

Figure 8: The ratios of the 32 Data Types for each of three Privacy Types. The denominator is the number of apps in the specific Privacy Type.

7 RQ2: Privacy Label Adoption and Changes

In this section we seek to answer RQ2, asking which factors affect the adoption of privacy labels and how and when does an app’s privacy label change? We first consider the context in which privacy labels were adopted, either being required because the app is new or has a version update, or if the developer simply updated metadata. Next we present details of if/when developers change previously posted labels. Finally,
we provide some case studies to illuminate both adoption and changing behavior over the study period.

7.1 Adoption Factors

Recall that adding privacy labels is mandatory for new apps that are added to the store following December of 2020 and for any app that submits a version update. However, pre-existing apps can also update their privacy labels without updating the app (i.e., increasing the version number) by simply submitting a revision to their App Store page to include labels. Figure 9 presents the differences in how these two types of apps are labeled, those without a version update (voluntary addition of privacy labels) to those with a version update or new (forced adoption of privacy labels). There are markedly different distributions in privacy label types. A much larger share of apps that were forced to apply a privacy label choose Data Not Collected as a label (50% vs. 42%). A similar trend is observed for other types.

These results suggest that developers voluntarily opting into privacy labels may be taking a more genuine approach to selecting labels as they were not required to do so. In contrast, developers that were forced to add labels may have thought of the process as onerous and simply an obstacle to the end goal of adding or updating an app. They simply selected labels for the purpose of expediting the process. The divergence in distributions may imply that many of the labels are in fact speculative and applied conveniently for a large share of the apps in the store, particularly given that many of the apps that have privacy labels are new apps, as opposed to version updates or voluntary updates. Moreover, the first labels that are applied are critical; we do not find that many apps 18,698 made changes to the privacy label during our observation period (more details below). The initial privacy labels persist, and so the accuracy of the first labeling is key.

7.2 Privacy Label Shifts

A total of 18,698 apps changed the Privacy Types of their labels. As presented in Figure 10, there are two common shifts. The largest is a privacy label shift from Data Not Collected to any of the other three Privacy Types (n = 15,804). Most often this occurs from Data Not Collected to Data Not Linked to You (n = 6,635), followed by Data Linked to You (n = 5,040), and lastly, Data Used to Track You (n = 4,129). When an app developer decides to change a privacy label (which is rare) from Data Not Collected, they are more likely to choose the less invasive of the Privacy Types, e.g., Data Not Linked to You. In contrast, the second common shift
is moving from a more invasive label (Data Used to Track You) to a less invasive one. Data Used to Track You (n = 11,027) shifted towards Data Linked to You (n = 4,884) and Data Not Linked to You (n = 4,806), and a small number (n = 1,377) moved from Data Used to Track You to Data Not Collected. Very few shifts (n = 3,611) involved changes from a Privacy Type where data is collected and/or tracked to Data Not Collected.

We also measured how the data categories and their associated Privacy Types changed for apps that had privacy labels. Recall that an app’s privacy label is multi-leveled, beginning with the Privacy Type (e.g., Data Not Collected or Data Used to Track You), and then under that, a developer can note the specific data categories being collected/tracked, as well as the purposes. Importantly, the Data Categories and Purposes can be changed without necessarily changing the Privacy Types.

When we observe shifts in Data Categories, developers almost always added new categories rather than removing existing ones. The most commonly added categories are Identifiers, Usage Data, and Diagnostics, but these were also the most commonly removed Data Categories. (See Table 1.)

Data Categories can also be moved between Privacy Types; for example, Contact Info may have previously been of the type Data Linked to You and is now Data Used to Track You. Similar to Data Categories that were added, Data Categories that were shifted most often between Privacy Types were Usage Data, Identifiers, and Diagnostics. Specific to these three Data Categories, the most prominent shifts are towards Data Used to Track You and Data Linked to You from Data Not Linked to You. This is in contrast to other Data Categories, where we more commonly observed a shift from Data Linked to You to Data Not Linked to You. It is unclear if these shifts indicate that developers are making their Data Categories more accurate or are attempting to obscure data collection practices of more sensitive data. That is, they are willing to note that data is collected, but do not want to indicate that it is actually linked to users.

We analyzed apps based on their App Store assigned genres to determine if that impacted shifts in Data Categories between Privacy Types. Games engage in multiple Data Categories shifts, more so than any other genres. The Data Categories that are most often shifted are Usage Data (n = 10,437), Identifiers (n = 692), Diagnostics (n = 362), Location (n = 299), User Content (n = 112), Purchases (n = 112), and Other (n = 78) Data Categories between Privacy Types. The audience of mobile app game users is “expansive” [45, 46] and is a lucrative market for in-app advertising, which may explain why so many Data Categories shifts occur [47].

Data Categories can also be assigned different Purposes when labels change; for example, a label where Identifiers were collected for App Functionality could change to Third Party Advertising. Across different Data Categories, labels most often change (or add) Purposes to App Functionality, Analytics, and Product Personalization. These shifts potentially indicate developers attempting to associate data collection practices with more beneficial purposes.

### 7.3 Case Studies

**U-Haul**  
U-Haul provides moving trucks, trailers, and self-storage rental services and lets users access their offering, reserve/pay for services, and manage their account through an iOS app [48, 49]. U-Haul’s App Store page [49] includes screenshots of the app which show that a user account on the app includes their Contact Info (Email Address, Physical Address), Financial Info (Payment Info), and that the app saved previous rental orders (Purchases) made using the account. While these screenshots are made available on the app’s page by the developer themselves, their self-reported labels on the same page state otherwise.

At the beginning of our measurement period, the U-Haul app had a Data Not Collected label, indicating that they did not collect any data from their users. This label is incorrect since the service relies on creating and maintaining user information, and offering purchases that are facilitated by gathering financial information from the user.

U-Haul retained this incorrect privacy label for a over a year during our measurement period, before they changed this composition in May 2022. The new label indicated that the app collects three data categories: (1) Usage Data that is

| Data Category     | Added | Removed |
|-------------------|-------|---------|
| Identifiers       | 8,576 | 2,585   |
| Usage Data        | 7,317 | 1,993   |
| Diagnostics       | 6,208 | 1,811   |
| Contact Info      | 5,439 | 1,765   |
| Location          | 5,489 | 1,900   |
| User Content      | 3,688 | 1,444   |
| Purchases         | 1,705 | 784     |
| Other             | 1,505 | 760     |
| Financial Info    | 1,781 | 654     |
| Search History    | 897   | 613     |
| Contacts          | 572   | 326     |
| Browsing History  | 472   | 427     |
| Health and Fitness| 395   | 139     |
| Sensitive Info    | 300   | 147     |
linked to users and used for Analytics; (2) Diagnostics data that is not linked to users (i.e., anonymized) and used for Analytics; and (3) Precise Location data that is not linked to users (i.e., anonymized) and used for Analytics and App Functionality. It is important to note that while the new label is more accurate, it is still incomplete. The screenshots and app description provided by the developer indicate that the app collects Contact Info, Financial Info, and Purchases, none of which are declared in the privacy label [49]. More alarming, the developer’s privacy policy [50] states that they collect not just additional details about the user’s Contact Info (Phone Number), Identifiers (Date of birth, Drivers License), and Sensitive Info (Biometric information: “Images of your face”).

First Command Bank Providing financial services aimed at American military families, the First Command Bank provides an app for their customers to access their checking, savings, and credit card accounts to check their balances, transfer funds, deposit checks, and pay bills [51, 52]. The screenshots and description of the app on the Ap Store indicate that the app requires users to create accounts where they can then link multiple bank and credit accounts, view and update them, and perform transactions. These interactions clearly require access to the user’s personal Identifiers along with their Financial Info and Purchases (i.e., transaction history).

At the beginning of our measurement period, the First Command Bank app had an elaborate privacy label that comprised 3 Privacy Types and 7 Data Categories – (1) Contact Info that is used to track users, (2) Purchases, Financial Info, Location, Contact Info, Identifiers, Usage Data, and Diagnostics, that are collected in an identifiable manner, i.e., are linked to users, and (3) Financial Info, User Content, and Usage Data, that are collected in an anonymized/unlinked manner [53].

The app retained this label until October 2021 at which point they updated their label to a single, Data Not Collected Privacy Type indicating that they do not collect any data. The app and service, as indicated by their website, do not reflect any discernible privacy or functionality changes. This developers therefore knowingly changed their labels to reflect completely erroneous data collection practices. At the end of our measurement period, the app retained this label, and was available for users to download.

Concours Avenir A competitive application service based in France, Concours Avenir helps streamlines the application procedure for 7 major French engineering schools [54]. The service lets students access education advice, testing services, information about schools. It helps them apply for and view results of the competition [55]. At the start of our measurement period, the app did not have a privacy label associated with it on the App Store. However, they adopted a label in October 2021. The first label was added without a corresponding version update, indicating that the developers voluntarily declared their data collection practices.

Their privacy label now indicates collection of Contact Info to track users and link to users, Identifiers linked to users, and finally Diagnostic data not linked to users. The privacy label spans multiple Privacy Types, in line with our findings (Figure 9) that apps adopting labels without a version update where more likely to include more Privacy Types.

Wordle! Ranked #2 in the Word Games category on the App Store, the Wordle! app [56] provides an alternative to the popular game owned by New York Times [57]. The app offers users an option to play the game multiple times a day and to compete against their friends. At the beginning of our measurement period, the Wordle! app did not have a privacy label. The privacy policy provided by the app’s developer, Lion Studios LLC, indicates that the service lets users create accounts and collects their registration and payment information [58].

The developer added a privacy label for the app in January 2022. Their privacy label adoption did not correspond with a version update, and their new label comprised two Privacy Types, indicating that they collect data that is linked to users and used to track users. Their label mentions the collection of 7 Data Categories, 5 of which are used to track users. This example also aligns with our previous findings that apps that voluntarily adopt a privacy label include more Privacy Types and are more likely to indicate collection of data that is linked to users and used to track users.

8 RQ3: App Metadata and Privacy Labels

In this section, we consider app’s metadata, such as content rating, app size, and price, as it relates to data collection practices in the privacy labels. Unless stated otherwise, all results are from the last snapshot (Run 50; October 25, 2022).

Content rating Apps’ content rating describe the age appropriateness of an app, e.g., is it for adults or children (i.e., 4+, 9+, 12+, and 17+), and are set by the developer based on Apple’s guidelines [59]. These content ratings should also comply with local policy requirements; for example, the Children’s Online Privacy Protection Act (COPPA) [60] in the US.
Most apps with privacy labels have a content rating of ages 4+ (n = 843,912; 75.9%), while only 13.5% (n = 150,354) of apps with labels have a content rating of ages 17+. Of apps with privacy labels, 15.8% (n = 133,615) have a 4+ content-rating and are labeled with Data Used to Track You, and 35.2% (n = 297,536) are labeled with Data Linked to You. For the 17+ content rating, 18.5% (n = 27,834) were labeled with Data Used to Track You and 45.3% (n = 68,121) with Data Linked to You. Refer to Figure 11 for full details.

Apps with ratings of 4+ or 9+ that are also targeted at children would be subject to COPPA compliance in the US and require consent from parents to collect data that tracks minors under the age of 13. We did not perform a manual review of these apps to determine if they are actually directed at children, but the fact that so many apps with a 4+ or 9+ content rating track data and would be available to children under the content rating guidelines (such as those used by parental controls) is problematic and worthy of further investigation.

**Rating count** Users can rate apps on a five-star scale in the App Store (even without leaving a review), and the magnitude of ratings offers a reasonable proxy for app popularity. Apps with over 100,000 ratings collect on average 19.25 (SD = 11.50, M = 17) Data Categories per app, while apps with fewer than 100,000 ratings only collect on average 7.24 (SD = 6.86, M = 5) Data Categories per app. Furthermore, 63.9% (n = 430) of apps with over 100,000 ratings were labeled with Data Used to Track You and 86.9% (n = 585) with Data Linked to You. This is a noticeably higher proportion of data collection for tracking and linking purposes than apps with fewer ratings. For comparison, for apps with 100–1,000 ratings, only 17.8% (n = 195,622) are labeled with Data Used to Track You and 37.8% (n = 415,698) with Data Linked to You. (See Figure 12.) These results indicate that more popular apps are more likely to report tracking and linking user data. Apps with more users may be monetizing their popularity [61].

**Release date** Apps released in 2021 (n = 299,440) were required to have a privacy label, and these apps make up
Figure 13: The ratios of top apps in app store genres for each of the four Privacy Types. The denominator is the number of apps with the designated app store genre that have a privacy label. This includes only apps placed in the top in genre categories.

27.0% of all apps with labels. Older apps have made progress in coming into compliance, but at the end of the data collection a little over half (53.04%; \( n = 524,958 \)) of apps released before the December 8, 2020 were privacy-label compliant. A significant share of older apps are still without labels, which may suggest that these older apps are no longer being supported with developer updates, or there is a lack of incentive for developers to make privacy label updates without being required to do so. Refer to Figure 14 for a detailed look at the number of apps with privacy labels by release year for each Privacy Type.

**App size** According to the privacy labels, larger apps collect and track more user data. This may be due to the fact that apps with larger footprints contain additional software libraries for this purpose. Additionally, game apps (as discussed below) are commonly tracking users and tend to require large downloads for graphics and other features. (See Figure 15.)

**App price** According to the self-reported privacy labels, free apps with in-app purchases are more likely to track and link to users’ identities, likely to generate revenues, than paid apps. Free apps report collect on average 7.30 (\( SD = 6.90, M = 5 \)) Data Categories per app, while paid apps only collect on average 4.18 (\( SD = 4.53, M = 3 \)) Data Categories per app. This is in alignment with Scoccia et al. [42], who made this comparison on a small subset of apps. These findings differ from the work of Han et al. [20, 21] who investigated free and paid apps in the Android market based on inclusion of third-party advertising software, finding no differences between free and paid apps. Refer to Figure 16 for full details.

**Top chart app genre** The Apple App Store offers categorization of apps into genres, such as Social Networking, Games, etc., and we analyzed the Privacy Type distributions for apps with labels in each of the genres. We found that Games apps are the most likely to track users, followed by Shopping, Music, Photo & Video, and Social Networking. Shopping apps are most likely to link data to users’ identities, followed by Magazines & Newspapers, Finance, Lifestyle, Sports, and Social Networking apps. Shopping apps are the most likely to collect data not linked to users’ identities followed by Magazines & Newspapers, Entertainment, Weather, and Lifestyle. Refer to Figure 13 for full details.
Figure 14: The number of apps released during a given year for each of the four Privacy Types. The gray bars show the total number of apps with privacy labels released in that year. The collection window includes apps through October 25, 2022.

Figure 15: The ratios of app sizes for each of the four Privacy Types. The denominator is the number of apps with the designated app size that have a privacy label. Apps that are larger in size are more likely to collect data, including data used to track and linked to users.

Figure 16: The ratios of app costs for each of the four Privacy Types. The denominator is the number of apps with the designated app cost that have a privacy label. Free apps are more likely than paid apps to collect data, including data used to track and linked to users.
Location data The collection and use of location data is a source of concern for users of mobile apps [62]. We found that the Location Data Category was reported under Data Used to Track You by 52,727 apps, under Data Linked to You by 127,464 apps, and under Data Not Linked to You by 129,006 apps. In total, 254,145 apps self-report collecting location data. However they only constitute 22.9% of the total number of apps with privacy labels. Kollnig et. al. [12] found that 49.2% of iOS apps request opt-in permissions for access to device location data. This suggests that either the apps that request access to location data are keeping the data local to the device, or that location data collection is underreported on the App Store privacy labels.

9 Discussion and Conclusion

This paper presents a large-scale, longitudinal evaluation of privacy labels in the Apple App Store. To accomplish this we collected and analyzed the privacy labels and other metadata for 1.6 million apps for over a year. Through this analysis, we explored the following research questions, whose answers we summarize below:

- **RQ1:** What are the trends of privacy labels adoption? There is a steady increase in the number of apps with privacy labels, 70.1% of apps have privacy labels as of October 2022, a 28% increase since the start of the measurement period. While more than half of the apps report some form of data collection, there is still a large share of apps (41.8%) indicate no data collection. The most common purposes of data collection, either linked or not linked, is Analytics and App Functionality, where Identifiers and Usage Data are the most common data categories.

- **RQ2:** What factors affect the adoption of privacy labels and how do they change? We identified a discrepancies in privacy labeling when app developers are forced, e.g., via a version update, to adopt a label compared to voluntarily applying a label, e.g., a meta-data update. App developers updating labels voluntarily are more willing to indicate broader classes of data collection then those forced, who are more likely to indicate data not collected. Moreover, when we observed 18,698 apps that changed their labels during the observation period, and when they do shift, most commonly they move towards more data collection.

- **RQ3:** How are different dimensions of apps (based on app metadata) selecting privacy labels? The metadata analysis indicated a number of interesting trends with respect to privacy labeling, including that more popular apps and larger apps self-report more data collection than less popular ones and smaller ones. There are also large numbers of apps with content-rating that applies to children performing data collection, which may be a violation of COPA if these apps specifically target minors. We also show that free apps self-report collecting more data than paid apps.

Based on these findings, we offer additional discussion and further interpretation below.

The high cost of free apps Many free apps are only free because they partake in the lucrative data collection and sharing practices. As we presented in Section 8, free apps collect, on average, three more categories of data than paid apps. When combined with other app metadata properties, the contrast is more stark. For example, free apps with more than 100,000 ratings (an indicator of audience size) collect on average 19.25 (SD = 11.50, M = 17) Data Categories per app. The large audience increases the surveillance surplus, which may make it harder for app sellers to resist collecting a wider range of data to increase profits. For instance, free Social Networking apps with more than 100,000 ratings collect an average of 23.64 (SD = 18.24, M = 22) Data Categories per app.

These findings differ somewhat from prior work by Han et al. [20, 21], where they used the inclusion of third-party libraries as a proxy for privacy behaviors, and compared free apps with their paid counterparts. While they found no clear difference in privacy behaviors between these pairs, our analysis looks at free and paid apps from an ecosystem-wide perspective. At the very least, our findings confirm that the popular free Games, Shopping, and Social Networking apps are also the top collectors of user data.

Empowering users Ideally, iOS users would compare the privacy labels of apps with similar functionalities and select the app that best satisfies their personal privacy preferences. However, there is evidence that users may not make such choices using install-time information. In many ways, privacy labels function similarly to install-time permissions from Android [27] as a pre-installation, one-time opportunity for review. And like install-time permissions, users are likely not sufficiently informed nor sufficiently motivated to take action at that time.

A second challenge is that the privacy labels are integrated into the App Store, not the iOS device itself. There are no mechanisms for users to review already installed apps, other than go to the App Store and select each app one by one. And even if a user were to perform this action, there is no
A mechanism for them to become aware of changes or updates in the privacy labels for apps over time. It remains unclear how and where privacy labels are intended to assist users in making informed decisions about their apps.

A question of accuracy There have been news reports [63] and research [37] about the inaccuracies found in App Store privacy labels. We illustrate in Section 7 that when apps are forced to add privacy labels due to a version change or as a new app they are more frequently providing the Data Not Collected Privacy Type, potentially out of convenience, expediency, or deception. Furthermore, we describe in Section 8 how 22.9% of apps with privacy labels report collecting location data, but research [12] has found that 49.2% of apps request access to location data. These discoveries suggest under-reporting of data collection via privacy labels. When reviewing a few apps manually, we observed apps that have a Data Not Collected label that conflicts with data collection practices outlined in their privacy policy. Future research is required to determine the full scope and nature of the inaccuracies in the privacy label ecosystem.

Without additional oversight from Apple and without negative consequences for inaccurate labels, developers may simply never be motivated to create labels that accurately reflect their apps’ data collection practices. A lack of credibility in the privacy label model will ultimately erode user confidence in the system and reduce the likelihood that market forces will force developers to develop more privacy-preserving applications. Inaccurate labels are also harmful to users as privacy expectations become misaligned with apps’ true data collection practices.

Communicating label updates to users When app developers update their privacy labels, as 18,698 apps did during our collection window, they tend to report more data collection. Users who have already installed and are currently running these apps on their devices are not notified that the privacy label has been modified. We contend that a mechanism that provides users with an easily understandable description of the changes to the privacy labels should be provided to users upon label update. One suggestion would be to display a notification to users the next time they open the updated app. The notification would also be useful for those applications that were installed by users before they had privacy labels, but have since labels adopted.

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