# Datasets on Mobile App Metadata and Interface Components to Support Data-Driven App Design


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Abstract: The global mobile device market currently encompasses 6.5 billion users. Therefore, standing out in the competitive scenario of application stores such as the Google Play Store (GPlay) requires, among several factors, great concern with the User Interface (UI) of the apps. Several datasets explore UI characteristics or the metadata present in GPlay, which developers and users write. However, few studies relate these data, limiting themselves to specific aspects. This paper presents the construction, structure, and characteristics of two Android app datasets: the Automated Insights Dataset (AID) and the User Interface Depth Dataset (UID). AID compiles 48 different metadata from the 200 most downloaded free apps in each GPlay category, totaling 6400 apps, while UID goes deeper into identifying 7540 components and capturing 1948 screenshots of 400 high-quality apps from AID. Our work highlights clear selection criteria and a comprehensive set of data, allowing metadata to be related to UI characteristics, serving as a basis for developing predictive models and understanding the current complex scenario of mobile apps, helping researchers, designers, and developers.


## 1 INTRODUCTION

Boasting more than 6.5 billion users globally, mobile devices are now indispensable for communication and technological interaction. The Google Play Store (GPlay)[1], the predominant app marketplace, features 2.6 million apps as of 2023. Concurrently, Android, the operating system associated with this app store, is installed on 70% of smartphones (Statista, 2023).

In such a competitive landscape, differentiating requires a focus on the quality of the User Interface (UI), which significantly influences the User Experience (UX) (Nielsen and Budiu, 2015). Accessing pertinent examples can elucidate market trends and best practices, thereby assisting designers and developers in refining their applications and enhancing user engagement (Deka et al., 2017).

Some works have developed datasets with thousands of UIs; however, few works create links between the graphic and textual elements presented in the interfaces, identifying, for example, interface components, essential items in the construction and understanding of the UX. The applicability of this knowledge is diverse and can serve as training data for models capable of generalizing knowledge, detecting apps similarity or generating interfaces from screenshots (Liu et al., 2018; da Cruz Alves et al., 2022).

This paper aims to demonstrate the construction process, structure, and characteristics of two Android app datasets: the Automated Insights Dataset (AID) and the User Interface Depth Dataset (UID). AID brings together metadata of the 200 most downloaded free apps from each of GPlay's 32 categories, totaling 6400 apps, with information beyond that presented by app stores. The UID brings a high-quality sampling of AID and delves into the identification of 7540 components separated into 50 types and the capture of 1948 screenshots of the interface of 400 apps. We used Google Material Design (GMD) components to create the set of standard UI components, as it is a relevant and popular design language used in the Android sys-


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tem and also some components from Android Studio[2] (AS), a widely-used Android development platform.

The paper is organized as follows: Section 2 presents work that developed or used mobile app datasets; Section 3 addresses the methodology adopted; Section 4 details the AID and UID datasets; Section 5 discusses limitations and threats to validity; and Section 6 highlights the results, contributions, and practical applications.

# 2 RELATED WORK

## 2.1 Mobile App Metadata Datasets

App stores present valuable app data, such as product descriptions and user reviews, that are fundamentally strategic for companies and developers. However, challenges such as GPlay's Anti-web scraping mechanisms impose barriers to collecting and analyzing this data.

In the past, (Prakash and Koshy, 2021) mined metadata from more than 2.3 million apps and games available on GPlay in 2021 and (Kabir and Arefin, 2019), used an "app crawler" to identify keywords present in GPlay app reviews. However, Appbrain[3] stands out as a comprehensive, updated, and auditable dynamic data repository of GPlay apps, offering insights beyond what is available on the app store (Harty and Müller, 2019; Crussell et al., 2014). This repository maintains information even on apps that are no longer available, offering historical data on the evolution of apps, being chosen, therefore, as a viable choice to overcome the challenges of GPlay.

## 2.2 Mobile UI Datasets

Large-scale mobile UI data repositories are essential for several applications, especially for data-driven model development. The Rico[4] dataset contains visual, textual, structural, and interactive design properties of 66 thousand screenshots from 9.7 thousand free apps (Deka et al., 2017). Furthermore, it served as a basis for other works such as (Liu et al., 2018; Wang et al., 2021) that map the components of a small subset of these screenshots, creating component identification models. In general, the goal pursued in component mapping is linked to the development of tools to assist the developer in searching for similar UIs to recommend components (Bunian et al., 2021; da Cruz Alves et al., 2022). Still, the few works that relate UIs to metadata have a limited mapping of components (Li et al., 2014).

In general, the UIs of popular Android apps are of better quality compared to other operating systems (Kortum and Sorber, 2015). Furthermore, works such as (Liu et al., 2018), which classify and categorize UI components using GMD as a basis, which aligned with the popularity of the Android language and system, were also chosen as the basis for our work.

Although the data presented in Table 1 show the magnitude of popular datasets linked to apps, to our best knowledge, no work relates the components of the UIs with the metadata, even those capable of identifying this link. Furthermore, there was no description of the criteria used to select apps in any datasets.

Table 1: Comparing existing app database ("?" the information was not addressed and "-" when not applicable).

| Authors | Year published | Number of | | | | | Manual analysis |
|---|---|---|---|---|---|---|---|
| | | App metadata | Categories | Components | Screenshots | Apps | |
| Li et al. | 2014 | 5 | ? | - | 8.4k | 8.4k | |
| Deka et al. | 2017 | 8 | 27 | - | 72k | 9.7k | ✓ |
| Liu et al. | 2018 | 8 | 24 | 25 | 720 | ? | ✓ |
| Kabir et al. | 2019 | 4 | ? | - | - | 10k | |
| Bunian et al. | 2021 | 1 | ? | 11 | 4.5k | ? | ✓ |
| Prakash et al. | 2021 | 10 | 48 | - | - | 2.3m | |
| Alves et al. | 2022 | 1 | ? | 9 | 365 | ? | ✓ |
| AID | 2024 | 48 | 32 | - | - | 6.4k | |
| UID | 2024 | 48 | 32 | 50 | 1.9k | 400 | ✓ |

# 3 METHODOLOGY

Based on other studies, this section describes the process of building both datasets (de Souza Lima et al., 2022; Liu et al., 2018). The subsection 3.1 discusses determining the sample population size and inclusion/exclusion criteria and introduces the datasets. The subsection 3.2 details AID and UID collection.

## 3.1 Requirements Analysis

### 3.1.1 Sample

We used GPlay as a basis to calculate the sample. The size of this sample (n) was calculated using the formula for finite populations (Fonseca and Martins, 2016) (Eq.1), where $Z$ is the abscissa of the standard normal distribution (fixed in the literature at 1.96); $\sigma$ is the population standard deviation (found at a value of 0.5535); $d$ denotes the sampling error (0.054243);

[2]https://developer.android .com/studio

[3]https://www.appbrain.com/

[4]http://www.interactionmining.org/

and, $N$ is the size of the total population of GPlay apps (2.6 million). Consequently, our study includes 400 apps for manual analysis, aligning with findings from other research (Liu et al., 2018; de Souza Lima et al., 2022).

$$n = \frac{Z^2 \cdot \sigma^2 \cdot N}{d^2(N-1) + Z^2 \cdot \sigma^2} \tag{1}$$

#### 3.1.2 Inclusion and Exclusion Criteria

When designing the inclusion and exclusion criteria for the datasets, we aimed to guarantee relevant, updated, representative, replicability and auditable data. Initially, we identify and extract the metadata from the 200 most downloaded free apps from each of GPlay's 32 categories. This number of 200 apps is considered the total number of downloads and coincides with the size of the ranking of each category on AppBrain, and the fact that they are free is linked to the greater possibility of analyzing the app, therefore justifying the choices (Deka et al., 2017).

This initial dataset, which contained the description and rating of 6400 apps, was the first version of the AID and the basis for the next steps of the work, which involved an iterative process of refining the selection shown in figure 1. We removed apps with no reviews and then calculated the average rating of 6150 apps, excluding apps $\leq 4.1$ stars, below average.

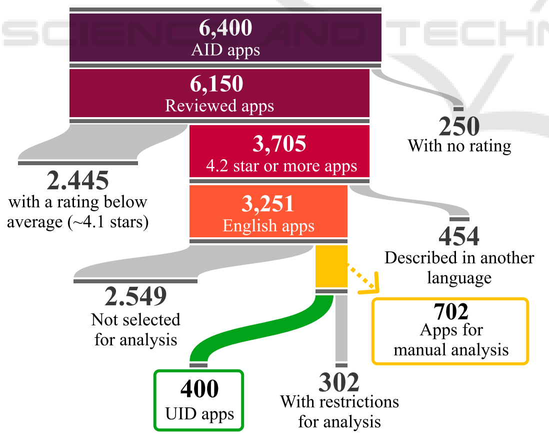


Figure 1: UID app selection journey from AID.

During the analysis of app descriptions, observations from comments and screenshots indicated that apps lacking an English description typically do not offer an interface in English either. Consequently, we utilized the Language Service API[5] to identify the language of the apps' descriptions. Apps with descriptions in languages other than English were excluded to ensure UI compliance.

Reaching a set of 3251 apps unevenly distributed across the categories, we created a set of restrictions aimed at the quality and relevance of the apps analyzed. Our restrictions excluded apps that are incompatible with the device; require a phone number; have execution errors; are a game; are locked in landscape mode; require specific data for sign-up; are region restricted; have a minimal UI such as frameworks, API and launchers; exceeded category distribution; do not allow screenshots; are paid; has a non-English UI; requires large files.

We primarily selected apps with the highest number of downloads that met the imposed restrictions, accounting for the uneven distribution across each category. As a result, out of the 702 apps analyzed, 400 formed the UID, while 302 were discarded due to various exclusion criteria, as shown in Figure 2.

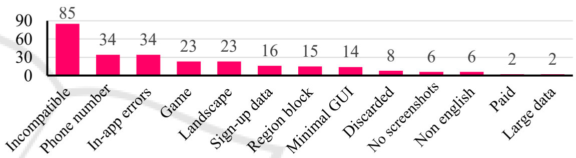


Figure 2: Restrictions encountered in app analysis.

#### 3.1.3 Data Categories

The data present in the UID and AID are presented in Table 2 and are divided into four categories: **GPlay Metadata** are extracted indirectly from the playstore; **AppBrain Metadata** complements and/or adds a layer of information to GPlay metadata; **Material Design components** are identifiers of GMD components in the UI; **Complementary components** are identifiers of interface components beyond those described by the GMD. In addition, each date in Table 2 has a number that refers to its type: [1] is discrete numeric; [2] is binary; [3] is nominal categorical; [4] is ordinal categorical; [5] is a text.

The captured components of each app are solely linked to the app's main functions and screens, excluding components that appear in, for example, configuration screens, login, tutorials, external elements, and ads. This choice aims to streamline the analysis time, as it is impossible to analyze each app deeply.

### 3.2 Data Management

#### 3.2.1 AID Collection

Carried out by one researcher, the initial 6400 app's data were extracted on November 3, 2023, by a de-

[5] https://developers.google.com/apps-script/reference/language?hl=en

Table 2: Categories and data collected.

| Category | Data collected |
|---|---|
| **GPlay Metadata**: is present in the AID and UID | GPlay Link[5], Name[5], Package[5], Developer[5], Category[3], Total Downloads[1], Description[5], Purchase Cost[1], Cost of In-App Purchases[5], Current App Version[4], APK size[4], Minimal Android Version[4], Maturity[4], Suitable for[4], User Rating[1] and Number of Ratings[1] |
| **AppBrain Metadata**: is present in the AID and UID | AppBrain App Link[5], Most Downloaded Position in Category[1], 10 Ranks by Country[5], Current Global Rank[4], Recent Downloads[1], Short Description[5], Description Language[3], Library Count[1], Positive and Negative Reviews Examples[5], Development Tools and Libraries[5], Contains Ad[2], Ad Libraries[5], Social Libraries[5], 12 Categories of Permissions[5], Release day[5], Installations milestones[5], Updates[5], Unpublished day[5], Category change[5] and Price over the time[5] |
| **Material Design com-ponents**: is present in the UID | Snackbar[2], Tool tip[2], Badge[2], Circular progress indicator[2], Linear progress indicator[2], Dialog[2], Full-screen dialog[2], Date picker[2], Dial time picker[2], Digital time picker [2], Side sheet[2], Bottom sheet[2], Radio button[2], Switch[2], Checkbox[2], Slider[2], Menu[2], Navigation rail[2], Navigation drawer[2], Navigation bar[2], Primary tab[2], Secondary tab[2], Segmented buttons[2], Chips[2], Top app bar[2], Extended FAB[2], Floating action button[2], Bottom app bar[2], Search[2], Carousel[2], List[2], Divider[2], Common button[2], Text field[2], Icon button[2]. |
| **Complementary com-ponents**: is present in the UID | Pre-loading indicator[2], Sound effects[2], Background music[2], Web component[2], Map view[2], Videos[2], Account required[2], Social interaction[2], Default night mode[2], Landscape mode[2], Text view[2], Card list[2], Grid layout[2], Images[2], Characteristic color[3] Collected date[5], Screenshots. |

veloped web crawler using Selenium[6]. On November 26, 2023, the remaining data was extracted by enhancing the web crawler. Finally, the raw data was transformed into the AID metadata.

#### 3.2.2 UID Collection

Two researchers carried out the UID collection, which was divided into four stages, which will be explained below. The researchers had previously passed blindness tests.

**Setting Parameters:** To maintain consistency and replicability, we decide to emulate using BlueStacks[7] an Android 11 device, with 4 CPU Cores and 8 GB of RAM, using the x86 and ARM architectures in 32 and 64 bits for greater compatibility. We also created emails and a set of fictitious data to fill out forms. We emulated New York, USA, as a geographic location.

**Pilot Test:** Composed of a subset of 33 apps from multiple categories and some complementary components, the test evaluated the feasibility of collecting and usefulness of the data and selected techniques. We identified and addressed crucial issues, refining both the UID and our collection strategy and developing a collection support tool that stores data before consolidation.

**Data Collection:** Following a pre-designed script, we started each collection section by installing around seven apps. We analyzed the apps, discarding those with restrictions, taking an average of 15 minutes for each app collected, with a maximum duration of 2 hours, to minimize errors linked to fatigue (de Souza Lima et al., 2022). The components were marked in the tool, and at the end of each section, the data and screenshots were individually analyzed and sent to an online repository. The definitive UID data collection began on November 12, 2023, and ended on February 5, 2024.

**Dataset Management and Analysis:** The UID management process did not present challenges, as the collection organization guaranteed the correct structuring of the dataset. The dataset analyses were carried out in Excel.

## 4 DATASETS

This section provides qualitative information, graphs, applicability, and observations pertinent to each database, with each aspect discussed in a separate subsection. The dataset files are accessible at https://doi.org/10.5281/zenodo.10676845 comprising spreadsheets named "Automated Insights Dataset (AID).xlsx" and "User Interface Depth Dataset (UID).xlsx". In addition to these files, the repository has a folder with screenshots of the UID apps divided by the ID of each app; a folder with a spreadsheet and screenshots of discarded apps; the source code of the web crawlers and tools developed; a folder that contains graphical representations of the UID components and textual representations of each component present in the UID and AID, allowing a better understanding of the criteria used.

### 4.1 Exploration of AID Characteristics

The AID dataset comprises insights from the top 200 most downloaded free apps across 32 GPlay categories, totaling 6400 apps. It stands out from other

[6]https://www.selenium.dev/

[7]https://www.bluestacks.com/

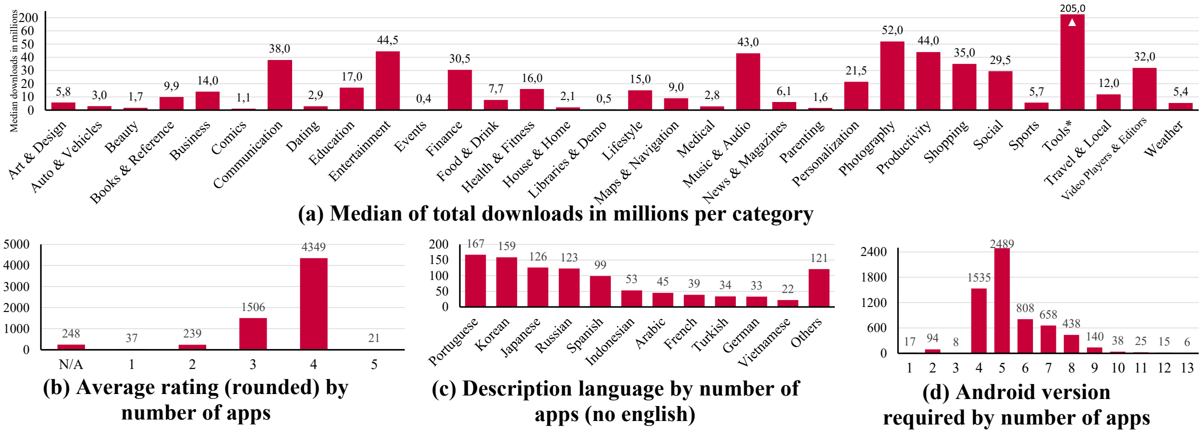


Figure 3: Set of relevant data present in the AID.

datasets by offering 48 metadata categories, as illustrated in Table 2. This section will explore pivotal metadata from AID and noteworthy discoveries from dataset analysis.

**Total of Downloads:** as observed in Figure 3a, we noted that ”Tools” stands out as the category with the highest median value, in absolute numbers, the combined total downloads of the apps in the category, ”Tools” category remains in the spotlight, with 190 billion downloads. We believe this occurs because this category comprises frameworks and libraries natively present on Android devices. The graph also displays the categories considered, matching those in the UID dataset.

**App Rating:** as illustrated in Figure 3b, most applications possess high ratings. Despite this, among the considered popular apps, 248 are unrated. Additionally, the AID dataset includes significant metadata such as ”Positive Reviews Examples” and ”Negative Reviews Examples”, featuring selected examples of 1 and 5-star reviews from GPlay.

**App Description:** GPlay limits it to up to 4000 characters. Furthermore, with the process described in section 3.1.2, we identified that 5379 (84%) are described in English, and Figure 3c presents the other apps described in another language. In AID, there is also a ”Short Description” generated by AppBrain, which more succinctly describes each app.

**Required Android Version:** as observed in Figure 3d, which disregards subversions, most apps aim at intermediate Android versions.

**Permissions:** are divided into 11 metadata representing categories close to those in the Play Store and one extra. Figure 4, which shows the most requested permissions, highlights the inconsistency where ”full network access” permission is requested by 6049 (95%) apps, although ”receive data from the internet” is only required by 4584 (72%) apps.

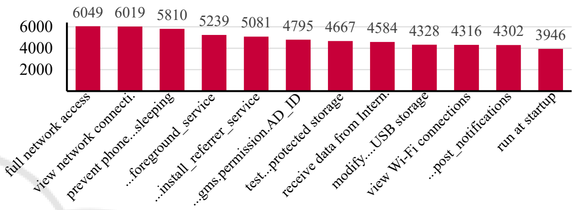


Figure 4: 10 most observed permissions required per app.

**Technologies:** divided into ”Social”, ”Ad” or ”Development tool” metadata, this metadata comes from AppBrain’s in-depth analysis of each app and allows an understanding of the development practices used, which can be applied to new apps (Crussell et al., 2014; Harty and Müller, 2019).

**Changelog-Derived:** is metadata derived from a limited historical record of the app; it is divided into ”Release day”, ”Installations milestones”, ”Updates”, ”Unpublished day”, and ”Price over the time”.

**Ranking:** is divided into three metadata: (i) ”Most Downloaded Position in Category”, which is a discrete numeric and measures the app’s global popularity among free apps; (ii) ”GPlay Current Global Rank”, which is categorical ordinal and formulated by GPlay; and (iii) ”Rank Country Category List”, which is textual and presents ten main GPlay Ranking specific to countries, categories, and costs.

## 4.2 Exploration of UID Characteristics

Covering 100 different data points, 48 coming from AID, and 49 binary identification of the presence of components in the UI of 400 apps, the UID maps trends among GPlay’s most popular software. The graph 5a presents the proportional distribution of apps depending on the category, as informed in the subsection 3.1.2. While the ”Tools” category has the highest number of downloads in the AID dataset, it is less prevalent in the UID dataset.

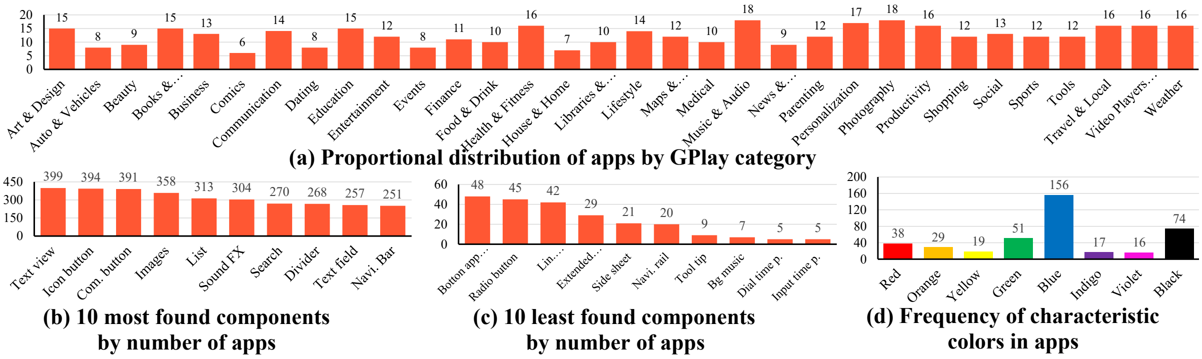


Figure 5: Set of relevant data present in the UID.

Figure 6 presents a dataset sample in which components indicated as existing may not be visible in the screenshots, highlighting the importance of analyzing apps, not just a single screenshot.

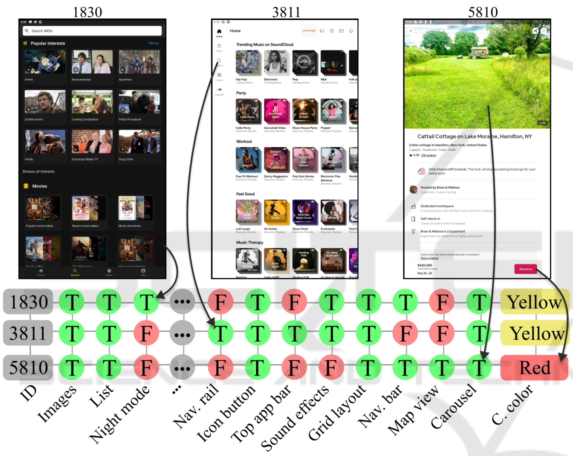


Figure 6: UID sampling for IMDB (1830), Soundcloud (3811) and Airbnb (5810) where F indicates that the component is not identified and T indicates that it is.

Figure 5b illustrates the prevalence of basic components among the 400 apps in the database. On the other hand, the graphic of Figure5c highlights that the components least found are those linked to more specific applications.

For a better understanding, we divided the components into five categories. These categories were created according to our observations during collection and mixed elements from the exclusive UID categories explained in Subsection 3.1.3. Below, each category will be better explained.

**Structural Components:** are vital for app UIs and include Text view, Common button, Icon button, Images, Floating action button (FAB), Extended FAB, Top app bar, Bottom app bar, Carousel, Grid layout, Card list, List, and Divider. These elements, present in all apps, are crucial for functionality and UX. Grid Layout, the most specific, is predominantly associated with entertainment apps like music and video.

**Navigational Components:** direct users to different windows and include Navigation rail, Navigation drawer, Navigation bar, Menu, Primary tab, Secondary tab, Search, Segmented buttons, and Chips. These components, present in 388 apps, are typically used independently, except for Search. The navigation bar, for instance, appears in 251 apps but is only paired with the Navigation rail in one. Additionally, Chips and Segmented buttons, intended for filtering according to GMD, often function as navigation aids. Similarly, the "Hamburger button" and "3 vertical dots" sometimes open new windows instead of the Navigation drawer or Menu, respectively.

**Input Components:** mainly found in app-specific configuration menus, comprise Full-screen dialog, Date picker, Dial time picker, Digital time picker, Text field, Side sheet, Bottom sheet, Radio button, Switch, Checkbox, and Slider. These components, given the collection criteria used, are uncommon, except for the Text field, found in 367 apps.

**Informative Components:** Informative components serve to inform users about processes and operations crucial for app usability and include: Circular progress indicator, Linear progress indicator, Pre-loading indicator, Badge, Snackbar, Tool tip, Dialog, and Sound effects. These components, present in 389 apps, are generally associated with specific actions or operations and are uncommon, given the analysis criteria. Progress indicators, such as the first three in this category, rarely coexist. The Pre-loading indicator often indicated content that differed from what was loaded, which was confusing.

**Other Components:** contrast with the tangibility and heterogeneity of other categories, being more abstract but equally important in UX. Some of the more abstract components are Account required, which identifies the need for user authentication for use; Social interaction, which identifies apps in which users can interact with each other; Web component, which identifies apps that present elements running outside the app's internal environment (such as browsers); Landscape mode identifies apps that non-mandatorily shape their components to display in this format; Default night mode identifies apps that predominantly have darker backgrounds and/or text colors; Characteristic color refers to a consistent color independent of the displayed content that characterizes an app's UI and is mainly seen in Navigational components, icons, badges, and primary tabs. Figure 5d shows which colors were collected and the frequency among the apps. For example, the app '5810' in Figure 6 showcases red as its characteristic color despite green being the predominant color of the screenshot. In addition to those previously mentioned, the "Other components" category, present in 353 apps (except color), also includes Background music, Map view, and Videos.

**Screenshots:** are focused on capturing numerous components per app in portrait mode. On average, each app has five screenshots, with a resolution of 1080x1920 pixels, 240 DPI, and an average size of 486 kilobytes. Despite emulating a GPS location, many Ad providers tailored recommendations based on our IP address, leading to uncensored ads in our native language in the screenshots.

# 5 THREATS TO VALIDITY

While the tools, management techniques, principles, and methodology employed in this study directly and indirectly bolster data reliability, it is crucial to acknowledge potential threats and limitations:

**Internal Validity:** The absence of a reevaluation process for previously analyzed interfaces, coupled with potential fatigue, heightens the risk of human errors. Although there were ranking changes for some apps and category alterations for ten apps between the initial and definitive collection phases of the AID, we preserved the initially identified categories and rankings. None of the apps that underwent category changes were included in the UID. Moreover, the metadata for the UID was extracted up to 50 days before the UI analysis. Given the dynamic nature of GPlay, such modifications threaten the study's validity.

**Construct Validity:** It is essential to highlight that the 400 UID apps follow the proportions of categories and restrictions according to the reduced sample of 3251 free AID apps, considering the quality criteria defined in Subsection 3.1.2, therefore not representing the actual distribution of GPlay apps. Furthermore, considering the interface variations, the scales adopted may bring nonconformities compared to some devices on the market, as the smartphone screen has a standardized resolution and proportion. Moreover, advertisements influenced by the regional and temporal context of the research may lead to replication variations.

**External Validity:** As an indirect source of information, AppBrain, which does not publicly provide the tools used to collect data from the app, may present non-conformities. For collecting the UID, we could perceive the consistency of data, even with restrictions on the information made available by GPlay. Still, we cannot generalize this consistency to AID since we do not access the GPlay pages of apps outside the UID. Furthermore, developers may misdescribe their apps, as we found apps requiring a newer version of Android, even though GPlay guarantees support for the version used in the emulator. Ratings, employed as a quality metric, may not necessarily reflect an objective assessment of an app's intrinsic quality, as they can be influenced by factors such as changes in billing practices or app architecture. Additionally, although our data extraction method can be applied to any app stores, our empirical results are specific to the free apps from GPlay. More work would be needed to ascertain whether these findings extend to other periods, app stores, or paid apps.

# 6 CONCLUSIONS

Our study focuses on providing a comprehensive collection of information from mobile Android apps. It presents two massive datasets, the AID and UID, targeting both app developers and researchers. This work distinguishes itself in the literature by detailing the process of selecting and collecting apps, increasing transparency, and valuing the replicability and continuity of the study.

The data collected is an innovation in mobile devices and design that analyzes the main functions of applications and the characteristic colors used in apps, going beyond a single screenshot. Furthermore, the amount of metadata collected presents an improvement, as, to the best of our knowledge, this is the work with the largest amount of different metadata collected to date. Analyzing this metadata alone presents great compression potential for popular GPlay apps. Additionally, the union of this metadata with the component data identified in the interfaces in the UID, which expands a widely used design pattern, characterizes an evolution of knowledge regarding the structure of the multiple screens of each app and its relationship with the information recorded by the developers and users in app stores.

Although our main focus in the work was the presentation of the datasets, future research could explore their insights and applications. In the AID analysis, we noticed many government apps indicating the inclination toward modernization and digitalization of government services. Despite this, few of these apps were analyzed to create the UID, indicating a possible lower concern about the usability of these apps. On the other hand, during the UID collection, we noticed the constant presence of Indian apps, indicating the quality and popularity of the services provided by several companies in India. Another point also noted during the collection was the dependence and independence of components that generally follow a pattern, different from the mistaken implementation by some apps, of different components and icons with functions different from those traditionally described, not necessarily being linked to the context of regional use of apps. In future analyses, machine learning techniques can be employed to analyze the relationships between app metadata and UI components, paving the way for automated app design and optimization.

It is possible to expand the datasets further, especially the UID. Quantitatively, we can cover an even more significant number of apps, delving into specific categories or applications, balancing or maintaining category proportions, and increasing data reliability. Additionally, we can extract more data or identify new ones from the available data, using techniques and tools to, for example, map components or classify the aesthetics of a screenshot (Liu et al., 2018; de Souza Lima et al., 2022).

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